DOCTORAL THESIS FOR THE DEGREE OF PHILOSOPHIAE DOCTOR

THE LONG-TERM ROLE OF HYDROPOWER IN ECUADOR'S POWER SYSTEM: ASSESSING CLIMATE CHANGE AND COST UNCERTAINTIES

PABLO ESTEBAN CARVAJAL SARZOSA

UCL Energy Institute
University College London
April 2019

To Jesus Christ my Lord and Savior.

For from him and through him and to him are all things.

To him be the glory forever.

Romans 11:36

DECLARATION

I, Pablo Esteban Carvajal Sarzosa, declare that the work presented in this thesis is my own. Information that has been derived from other sources, I confirm has been clearly indicated in the thesis.

London, April 2019

Pablo Esteban Carvajal Sarzosa

ACKNOWLEDGMENTS

To start, I would like to thank my wife, Elba Sánchez de Carvajal, for her support and for the many sacrifices she has had to make during the time I was reading for the PhD. Without her unconditional love, this journey would have been extremely difficult if not impossible. *Elby, fuiste, eres y serás el amor de mi vida. Esto, es para ti.*

I am grateful to my supervisors Dr. Gabrial Anandarajah and Prof. Yacob Mulugetta for their constant guidance and putting their enlightening experience at my disposal.

To my parents, Pablo and Julieta, who taught me the value of knowledge and hard work, this achievement is fruit of your efforts.

To my Irish-Ecuadorian family, Peter, Nidya, Anthony and Tío Guido, you have been an immeasurable blessing since day one in London. You have taken us in as your adoptive children and looked out for us in the day-to-day battles.

A big thank you to my colleagues at the UCL Energy Institute for their encouragement, advice and good laughs; particularly, Bernard Tembo, Jennifer Cronin, Francis Li, Julia Tomei, Alvaro Calzadilla, Elsa Barazza, Dayang Abu Bakar, Maragatham Kumar (Maggie), Virginia Gori, Tobias Reinauer, Priscilla Carvalho-Lapa, Baltazar Solano, Joël Guilbaud, Isabel Miño and Lilia Caiado.

To my sponsor, the Ecuadorian Secretariat of Higher Education, Science, Technology and Innovation (SENESCYT), for believing that educating Ecuador's youth is the key for development. Without your support, studying at one of the world's leading universities, would have only been a dream.

Finally and more importantly, I would like to show my gratitude to the Lord for giving me life, salvation and wonderful opportunities close to the people I love.

ABSTRACT

Hydropower is the leading source of renewable electricity generation worldwide. Traditionally, hydropower has been perceived as a cheap, reliable and a low greenhouse gas emitting energy source. However, evidence suggests that, given hydropower's dependency on the hydrological cycle, it could be particularly vulnerable to the effects of climate change. In addition, hydropower infrastructure has shown to be prone to significant cost overruns and delays, due to the inherent complexities that accompany its deployment. Previous research has quantified these issues but little investigation has taken place to assess them in an integrated manner.

The interest of this research is to assess how assumptions about climate change, policy and costs can induce shifts in generation portfolio optima, particularly of power systems that are based or plan to be based on hydropower in the long-term. For this purpose, a series of hydrological, hydropower and energy system models have been developed in order to take these factors into account, and search generation alternatives regarding technical characteristics (i.e. power system operation, energy system configuration, demand), economic specificities (i.e. technology costs, resource prices, cost risk) and geospatial factors (i.e. water resource distribution, precipitation, climate change). The proposed method is illustrated with a case study for the Republic of Ecuador until 2050, a South American country that relies heavily on hydropower and plans to continue harnessing its potential in the future.

Findings have identified that hydropower will remain an important least-cost and low-emitting electricity source in Ecuador's future, however its share in the electricity generation matrix could vary greatly. Furthermore, portfolio analysis has revealed the trade-off between generation portfolio cost and risk. Suggesting that shifting away from run-of-river hydropower, gas and oil-fired generation towards a system with larger shares of hydropower with reservoir, solar PV and geothermal energy can help hedge the power system against the uncertainties of climate change, fossil fuel price volatility and electricity infrastructure cost overruns. Failing to diversify the power system could create a lock-in to natural gas. This research adds to the literature seeking to provide insights for new hydropower developments particularly concentrated in emerging economies of South East Asia, South America and Africa.

IMPACT STATEMENT

The research methodology and results presented in this thesis have beneficial impacts both inside and outside academia. Regarding impacts for academia, the methodology presented in this research is comprehensive in its treatment on modelling hydropower in an energy system optimisation model. The particular characteristics of hydropower in terms of technology type, operation, potential and investment profile are studied systematically, which sets a good practice benchmark for modellers looking into representing hydropower. In addition to this, two of hydropower's long-term challenges, i.e. impacts of climate change and construction cost overruns, have been approached with novel methods that give insights about the level of uncertainty these issues pose for hydropower development. While most power capacity expansion studies usually consider few scenarios of climate change impact from average climate projections (if any), this study draws these scenarios from a large ensemble of long-term climate projections that have recently been made available by the climate modelling community. Regarding construction costs of hydropower, while most studies approach possible cost overruns in a deterministic manner, this thesis has incorporated cost overrun risk into the optimisation process of the energy system model as well as retrieving cost overruns statistics that have likely been made available for several power generation technologies.

The benefits beyond academia fall on the realm of long-term energy policy design. This research informs a number of Governments in the developing world that rely on or are planning to develop large hydropower infrastructure, such as Ecuador, Brazil, Colombia, Zambia, Ethiopia, Myanmar and the Democratic Republic of Congo, to name a few. Although results show that hydropower can remain as an important generation sources in the future, the status-quo of cheap and reliable large hydropower is challenged. Non-hydro renewable energy can also be used to supply rapid growing demand, keep emission low and hedge against risks, while failing to consider them can lead to lock-ins to carbon-emitting and volatile fossil fuel-based generation. The implications for policy in this study are not by any means prescriptive and wish rather to present policy makers a range of alternatives. It is expected that this research persuades energy ministers in developing countries to move beyond *one-of-a-kind large strategic projects* towards the idea diversified *strategic generation portfolios*.

PUBLICATIONS

Some findings of this thesis have appeared previously in the following peer-reviewed publications, which have also been authored by the author of this PhD thesis:

1. **Carvajal PE**, Anandarajah G, Mulugetta Y (2019), A portfolio theory approach to assessing uncertainties in power system planning - A case study for Ecuador. *Energy Economics* (Under review)

2. **Carvajal PE**, Li FGN, Soria R, Cronin J, Anandarajah G, Mulugetta Y (2019), Large Hydropower, Decarbonisation and Climate Change Uncertainty: Modelling Power Sector Pathways for Ecuador. *Energy Strategy Reviews*

3. **Carvajal PE**, Anandarajah G, Mulugetta Y, Dessens O (2017), Assessing uncertainty of climate change impacts on long-term hydropower generation using the CMIP5 ensemble - the case of Ecuador. *Climatic Change*

The core work in all articles mentioned in the list above has been done by the author of this thesis and showcase the methods and results obtained using the models developed solely by the author of this thesis. In article 1, Anandarajah G and Mulugetta Y are the author's PhD supervisors and contributed with improvement on the clarity of the text. In article 2, Li FGN contributed with improving text related to scenario narratives, Soria R provided important background information for Ecuador's energy system, Cronin J contributed with the discussion about climate change impact on energy systems, Anandarajah G and Mulugetta Y contributed with improvement on the clarity of the text. In article 3, Anandarajah G and Mulugetta Y contributed with improvement of text while Dessens O contributed providing insights on how to read and process large ensembles of climate projection data.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

LISTINGS

LIST OF SYMBOLS AND ACRONYMS

AR5	Fifth Assessment Report of the IPCC
ARCONEL	Agencia de Control y Regulación de Electricidad, regulator of the Ecuadorian power sector
bpd	Barrels per day
CELEC	Corporación Eléctrica del Ecuador, grid operator of the Ecuadorian power sector
CMIP5	Coupled Model Inter-comparison Project Phase 5
CO_2e	Carbon dioxide equivalent
GCM	Global Circulation Model
ESOM	Energy system optimisation model
EU	European Union
GHG	Greenhouse Gas Emissions
HFO	Heavy fuel oil
IEA	International Energy Agency
INDC	Intended Nationally Determined Contribution
IPCC	Intergovernmental Panel on Climate Change
IRENA	International Renewable Energy Agency
MVPT	Mean Variance Portfolio Theory
NDC	Nationally Determined Contribution
PET	Potential evapotranspiration
PJ	Petajoule
ppm	parts per million
SRREN	Special Report on Renewable on Renewable Energy of the IPCC
SRES	Special Report on Emission Scenarios of the IPCC
WCRP	World Climate Research Program
WEC	World Energy Council

Part I

INTRODUCTION AND LITERATURE REVIEW

1

INTRODUCTION

1.1 MOTIVATION FOR THIS THESIS

Hydropower is the world's largest single source of renewable electricity, producing around 17% of the world's total electricity (IEA, 2016b) and two-thirds of all renewable electricity generation (IHA, 2018). Hydropower's commercial maturity and reliable energy production makes it an attractive alternative for fossil fuel-based technologies. It dominates the electricity mix in several countries – developed or developing – by providing significant amounts of clean, renewable electricity. The large-scale global deployment of renewable energy is necessary to achieve deep reductions of greenhouse gas (GHG) emissions (IPCC, 2014d), with the aim of mitigating climate change by staying well below the 2°C average atmospheric temperature by the end of the century, as laid out in the Paris Agreement (UNFCCC, 2015a). For countries with significant hydropower potential, the technology is expected to play a major role in the energy transition needed to meet Nationally Determined Contributions (NDCs) (UNFCCC, 2015a) as well as meeting the 7th goal (100% energy access for all by 2030) of the United Nations' Sustainable Development Goals (SDG) (UN, 2015).

Hydropower's extreme flexibility is a strong asset for power systems, and will be vital to accommodate and facilitate the growth of variable renewable electricity (VRE) technologies such as wind power and solar photovoltaics. Thus becoming an important system management component capable of ensuring reliable and flexible renewable supply. However, while hydropower can help mitigate GHG emissions, the impacts that climate change will have on the availability of runoff in the future can impact the production from hydropower facilities. According to Schaeffer et al. (2013), this fact originates a paradox that has two sides. The first one has been extensively studied, i.e. the role of hydropower to reduce emissions in a low-carbon future to mitigate climate change; however, the second part, just recently has been started to surge in the international scientific community, i.e. the impacts that climate change may have on hydropower itself and on other sources of renewable energy (DOE, 2015).

Impacts that a changing climate can cause are usually not taken into consideration in conventional energy system models that are used to inform energy planners in the design of reliable, secure and least-cost electricity investment portfolios (Lucena, 2010). The presumptions taken in the planning of the operation and expansion of an electricity system based on hydropower, usually consider that climatic variables are stationary in the long-term (i.e. that their statistic properties remain constant over time and are similar to the historic trend). Under this assumption, hydropower could very well offer the lowest generation cost over its technical lifetime and effectively mitigate GHG emissions. However, research shows that future electricity generation from hydropower not only faces uncertainties associated with the current inter-annual variability of runoff patterns but there are also considerable discrepancies around the impact that climate change will have on the magnitude and direction of precipitation and other hydroclimatic variables (Blackshear et al., 2011; Cisneros et al., 2014). This reflects on several dimensions of energy security, mainly on the issues of security of supply, environmental sustainability and affordability, which are main topics of today's public discourse on energy policy (van Vliet et al., 2016b).

While climate change and the consequent uncertainty of available runoff for hydropower generation is a challenge for the energy system, there is an additional source of uncertainty that haunts the expansion of hydropower infrastructure and needs inclusion in long-term energy planning, i.e. the uncertainty of its investment cost. Capital cost of electricity generation infrastructure is an important parameter considered by energy models. All electricity generation technologies can be susceptible to project cost overruns; however studies have identified hydropower as the technology with largest average cost overruns and delays compared to other technologies (Callegari et al., 2018; Köberle et al., 2018; Sovacool et al., 2014b). In addition, its further deployment still faces regulatory, financial and social acceptance issues – particularly in large scale projects with negative experiences regarding hydropower's socio-environmental impact (Anderson et al., 2018) and the cost escalation caused by their inherent construction complexities (Ansar et al., 2014).

Given that geotechnical conditions cannot be precisely assessed until after the construction of the project begins, hydropower presents difficulties during the construction phase including unforeseen excavations, construction problems, in addition to social and environmental concerns (Bacon and Besant-Jones, 1998; Anderson et al., 2018). This creates significant uncertainty on whether hydropower will be available on time to meet demand and within the planned construction budget in the short-term, a fact that can have important long-term development implications for countries that rely or plan to rely on hydropower as their largest source of electricity generation.

In this context, the interest of this research is to investigate how these two detailed sources of uncertainty i.e. climate change and construction cost overruns, impact the production of hydropower, the power sector and the integrated energy system in the long-term. This research is related to studies that focus on the global challenges of renewable energy deployment (such as IEA, 2014a; GEA, 2012) and research that has sought to quantify the impacts of climate change on hydropower at national (Seljom and Tomasgard, 2015; Teotonio et al., 2017), regional (Golombek et al., 2012; Parkinson and Djilali, 2015) and global levels (van Vliet et al., 2016a; Berga, 2016). Furthermore, by studying the uncertainty of electricity infrastructure cost overruns a contribution is made to research that seeks to assess the risk hedging potential of different configurations of power generation portfolios (Awerbuch and Yang, 2007; Vithayasrichareon et al., 2015; Pye et al., 2015). As a result, the findings could help increase the uptake of other alternative non-hydro renewable energy systems as a strategy to develop a more diversified and robust power sector.

While this research sets out to explore the development of an energy system which depends heavily on hydropower with a specific case study for the Republic of Ecuador, it is believed that the methodology and insights from this work are valuable and replicable for strategic energy planning in other hydropower-dependent states or those planning large-scale hydropower development, which may well in turn have important implications for both their future socio-economic development, their energy security and their potential decarbonisation efforts: with this present work it is intended to expand this scientific literature.

1.2 RESEARCH QUESTIONS

A set of research questions have been identified to guide the thesis based on the research gaps that were identified in the literature review in Chapter 2 on page 23:

1. How broad is the uncertainty of hydro-climatic variables portrayed in a large ensemble of climate projections and the impact on the availability of runoff for hydropower generation?

2. How does hydropower output variations due to climate change impact the long-term least-cost power system development pathway?

3. How does incorporating recurring uncertainties such as the volatility of fossil fuel prices and the capital cost of electricity infrastructure impact the investment portfolio for the power sector?[1]

This research is divided in three consecutive themes. The first theme, which is tackled by the first research question, focuses on the uncertainty of hydro-climatic variables at the season and annual level and how this impacts inflow into the largest hydropower stations in Ecuador over this century. This theme paid particular attention on the discrepancies found among long-term projections derived from climate models. The second theme, which is tackled by the second research question, focuses on how the uncertainty of hydropower output impacts the least-cost energy portfolio of Ecuador by 2050. For this purpose, a long-term energy system optimisation model (TIMES-EC) was developed which represents the whole energy sector of Ecuador (supply and demand) and focuses on the particularities of hydropower for electricity generation. Finally, the third theme, which is tackled by the third question, integrates further uncertainties – the volatility of fossil fuel prices and the uncertainty of electricity infrastructure capital cost – into the energy system optimisation model.

1.3 CONTEXT

1.3.1 *Status and potential of hydropower*

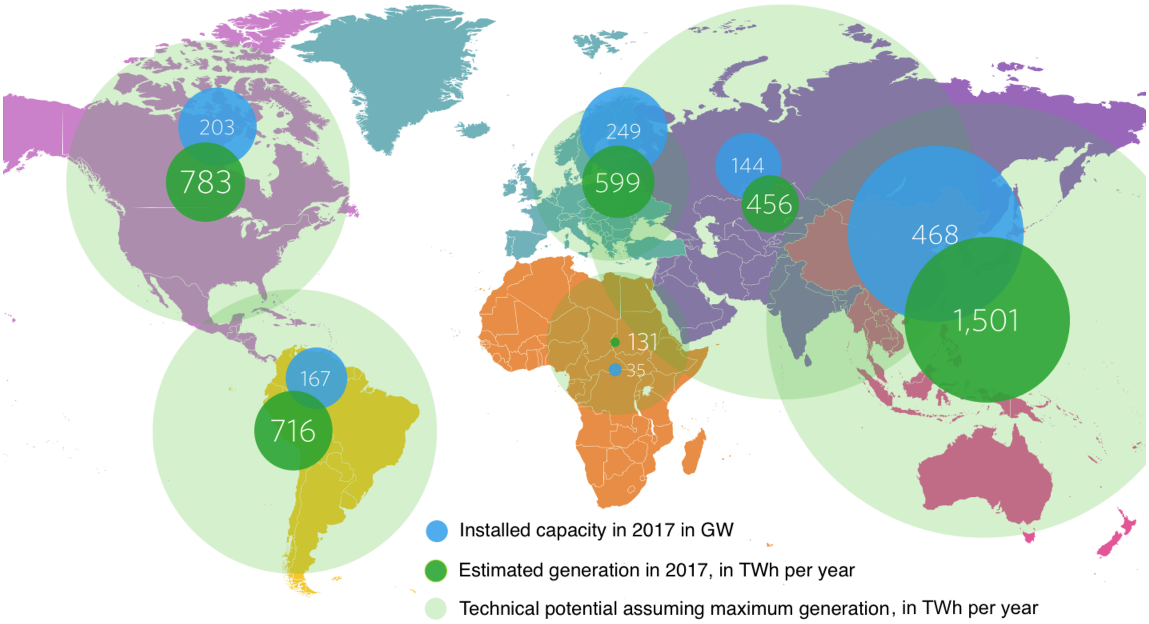
1.3.1.1 *Global level*

The International Hydropower Association (IHA) reports that electricity generation from hydropower reached an estimated 4,185 TWh in 2017, the highest ever contribution from a renewable energy source (IHA, 2018). Only in 2017, 21.9 GW of hydropower capacity was commissioned, that allowed reaching a global capacity of 1,267 GW. Around 160 GW of hydropower capacity are currently under construction, and more than 1 GW are planned. Figure 1.1 on the next page shows hydropower capacities and estimated generation by region in 2017. Six countries (China, United States, Brazil, Canada, India and Russia) together produce over half the world's hydropower generation. China has taken centre stage for hydropower capacity (319 GW) accounting for almost the combined capacity of the next five leading countries, as shown in Table 1.1 on page 8.

Hydropower has been extensively implemented in developed countries, while developing countries still have a long way to go. The World Energy Council (WEC) considers

1 Recurring uncertainty is characterised by conditions that are periodically recurring and in which knowing the past or current value of the parameter does not resolve the uncertainty for the future.

Figure 1.1: Hydropower capacity and generation by region



Source:IHA (2018)

hydropower to be in an upsurge at a global scale, with new developments particularly located in emerging markets and less developed countries. New developments are concentrated in East Asia (particularly China), South America and Africa (WEC, 2015b). In the most recent study of Gernaat et al. (2017), the global technical and economical potential of hydropower is assessed and valued at 9,500 TWh yr^{-1}(below 5 US¢ per kWh). Developing regions of Asia and South America have only tapped between 20% and 30% of the hydropower potential, while Africa is an extreme case, where only 7% of economically feasible hydropower potential has been developed (Berga, 2016). The drivers for the upsurge in hydropower development in these regions include mainly the increased demand for electricity of under-served populations and a growing industrial base, in addition to a set of ancillary services that hydropower infrastructure offers, such as water supply, flood protection, drought management, irrigation and climate change mitigation and adaptation solutions.

Table 1.1: Top hydropower capacity and generation as of 2017 by country

	Total capacity end of 2017 (GW)	Added capacity in 2017 (GW)	Production (TWh)
China	341	9.1	1,194
USA	103	0.3	322
Brazil	100	3.3	401
Canada	81	0.1	403
India	50	1.9	135
Russia	48	0.3	179
Total top six	723	15	2,634
Total world	1,267	21.9	4,185

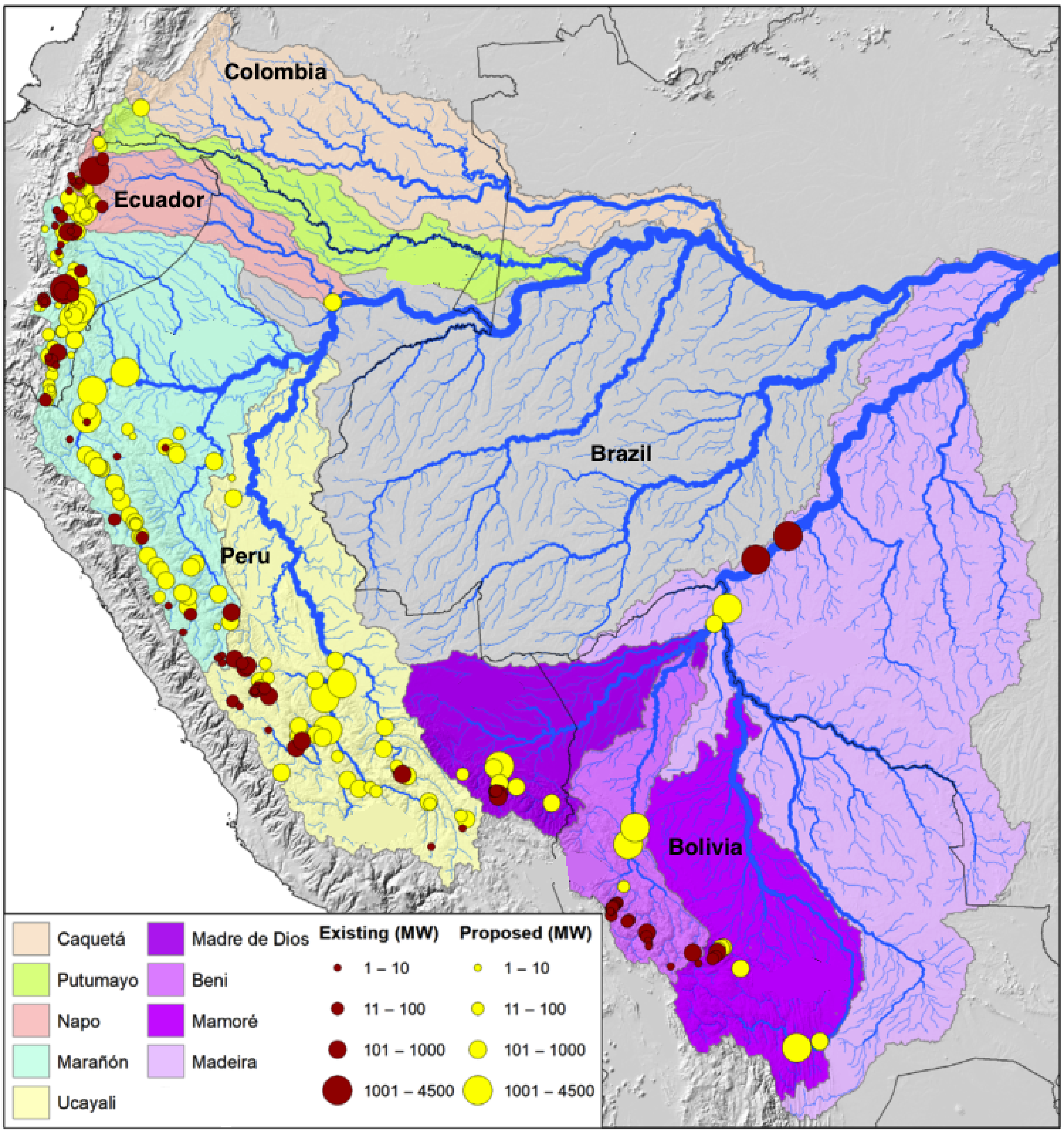
Source: IHA (2018)

1.3.1.2 *South America*

South America occupies a special place among the developing regions that benefit from hydropower and is a key market for hydropower development. In contrast to other regions, hydropower is the main source of power supply and forms the backbone of South America's electricity system, providing 63% of total electricity generation (IEA, 2016b). Brazil, the region's largest economy, leads the continent in both installed capacity (100 GW) and new capacity additions (3.3 GW in 2017), supplying 62% of the country's electricity needs in 2015. Other South American countries with high shares of hydropower generation include Ecuador, Colombia, Venezuela and Paraguay, with over 80% of hydropower generation in their electricity mix. In many other neighbouring countries over half of electricity generation is from hydroenergy sources (IADB, 2017).

Within South America, the Amazon river basin holds the largest untapped potential in the region (Gernaat et al., 2017; Schaeffer et al., 2013), particularly in the subregion known as the Tropical Andes (or Andean Amazon) located in the North East of the continent (see Figure 1.2 on the next page). The geographic scope of the Tropical Andes spans five countries – Bolivia, Brazil, Colombia, Ecuador and Peru – and holds the tributaries that flow down from the Andes mountains to the Amazon river. High annual precipitation coupled with rugged topography creates significant potential for hydroelectricity across the Tropical Andes (Herzog et al., 2011; Buytaert et al., 2009). According to official planning reports, countries that share the Tropical Andes emphasise hydropower as the centrepiece of medium and long-term plans to meet future energy demands. Latest studies have accounted for over 300 hydropower dam projects in the region, corresponding to hydropower stations in operation, under construction and in various stages of planning (Finer and Jenkins, 2012a; Anderson et al., 2018; Winemiller et al., 2016). Table 1.2 on page 10 shows existing and proposed hydropower dams in the Andean Amazon classified by country and size (installed generation capacity). As

Figure 1.2: Hydropower stations existing or under construction (red) and proposed (yellow) in the Andean Amazon river basins



Source: Anderson et al. (2018)

Table 1.2: Existing and proposed dams on Andean-origin rivers in the Amazon, classified according to country, number and size

Country	Existing/in construction		Proposed	
	Number	Total MW	Number	Total MW
Colombia	0	0	1	687
Ecuador	31	3,766	64	10,710
Peru	86	2,838	84	32,482
Bolivia	25	903	11	12,861
Brazil	2	6,450	–	–
Total	144	13,957	160	56,740

Source: Anderson et al. (2018)

can be seen in Figure 1.2 on the previous page, most of proposed new projects are in Ecuador, Peru and Bolivia who benefit from the elevation gradient that hydropower needs, which is not the case for the relatively flat Brazilian Amazon where projects would require large, shallow reservoirs that are prone to sedimentation and flooding of vast areas (Lucena et al., 2013).

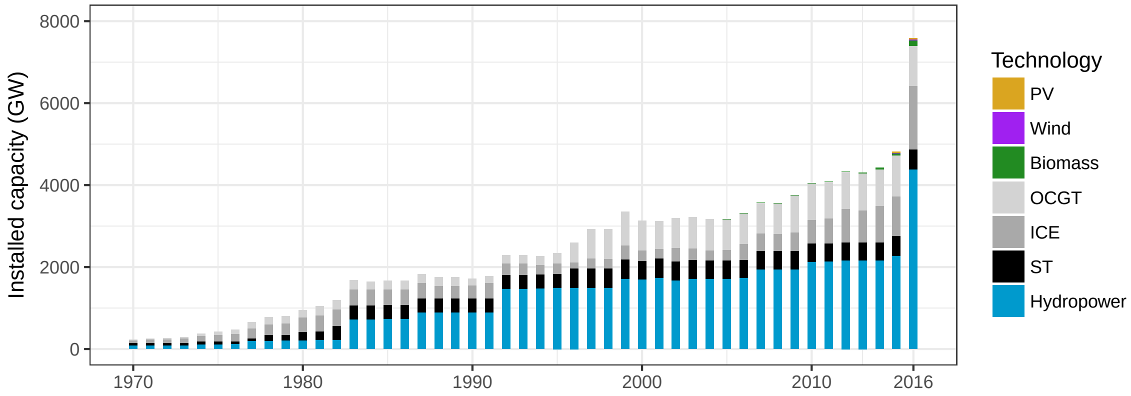
1.3.1.3 *Ecuador*

Over the past decade, Ecuador's energy policy has incentivised a doubling of its hydropower capacity. Between 2007–2017, the country invested close to $US 6 billion in eight flagship projects with a total installed capacity of 2,832 MW (The InterAmerican Dialogue, 2016). According to the International Hydropower Association (IHA), the country ranked third after only China and Brazil for countries that added new capacity in 2016 (IHA, 2017). Two large-scale projects located in the Amazon region make up most of this new capacity and both were inaugurated in 2016: Coca Coda Sinclair (1,500 MW) (Lopez, 2013) and Sopladora (487 MW) (CELEC, 2018b). The remaining six flagship projects are already in advanced construction stages and will be fully operational by 2020. Due to these large hydropower projects, installed capacity almost doubled, as can be seen in Figure 1.3.

According to the 2016-2025 Electricity Master Plan (MEER, 2017a) and the 2016-2040 National Energy Agenda (MICSE, 2016a), the Ecuadorian's government main energy policy is to consolidate hydropower as the most important source of electricity over the next few decades. The deployment of large hydropower has also recently become the cornerstone of Ecuador's INDC, presented at COP21 in Paris (UNFCCC, 2015b). Techno-economic hydropower potential[2] is estimated to be 22 GW of which only about one-fourth has been tapped by 2017 (ARCONEL, 2015). Most recently, the Ministry of

2 Techno-economic hydropower potential, in the Ecuadorian context, refers to the total capacity of hydropower projects with technologically feasible construction complexity at reasonable or industry-standard investment costs (MEER, 2017a).

Figure 1.3: Ecuadorian installed capacity 1970-2016



Note: OCGT is open-cycle gas turbines, ST is steam turbine, ICE is internal combustion engine and solar PV refers to utility scale solar photovoltaic.

Environment of Ecuador (MAE), has recently launched a project to assess the vulnerability of six large hydropower systems to climate change (MAE, 2018). However, reviewing the methodology proposed for this project it has been evidenced that it will only consider only few climate change projections and will assess hydropower stations on a plant-by-plant basis, leaving out the interactions with the broader power and energy system. Therefore Ecuador is considered as an interesting case study of a developing country, in which hydropower's future role is of utmost importance and where impact studies related to its deployment are of relevance.

Regarding the issue of capital cost uncertainty for hydropower technology, the Ecuadorian Government's construction of hydropower infrastructure during the last decade has already evidenced steep cost overruns. According to official data from the Government, the cumulative cost of the eight 'flagship' hydropower projects that the Government started construction of between 2010 and 2012, with total cumulative capacity of 2,832 MW, has had an average cost overrun of 26% (US$ 1,520 million) when compared to the budgeted and initial contract costs (US$ 5,850 million) (Villavicencio, 2015). Some of these hydropower projects have even incurred cost overruns that exceed 50% and also have significant delays; only three of the eight flagship projects expected for 2016 have been commissioned and have initiated operation (El Comercio, 2016). As these cost overruns and delays continue, consumers (or the Government) may have to pay higher prices to keep the lights on, evidencing that the uncertainty of constructing complicated large hydropower projects does have an impact on mid and long-term energy prices.

1.3.2 *Hydropower technology and costs*

Hydropower stations generate electricity by harnessing energy from moving water. Hydropower is a mature technology, which is well understood by energy planners and grid operators globally. Commercial technologies transform hydraulic energy into mechanical energy by means of a turbine which is coupled to an electricity generator. Conversion efficiencies from hydraulic to electrical energy are high, between 90 – 95% (WEC, 2016). Hydropower infrastructure is long-lived (over 75 years) and there are significant opportunities for upgrading or refurbishing the electro-mechanical equipment of existing hydropower stations and powering non-hydro dams (e.g. irrigation and flood control or domestic sewage water), particularly in markets where potential has been almost fully tapped (United States and Western Europe) (IHA, 2018).

1.3.2.1 *Types of hydropower*

Most commonly, hydropower stations partially block the water flow of a river and flood an area upstream to create a reservoir. This structural characteristic of hydropower plants i.e. their dam typology (Egre and Milewski, 2002), allows to classify hydropower schemes in:

RUN-OF-RIVER: A facility that utilises some or all of a river's flow to produce electricity without impounding any significant amount of water upstream. However, a small dam is still required to ensure that enough water enters the penstocks connecting with the turbines located downstream. The reduced storage capacity of run-of-river hydropower makes it more vulnerable to variations in the flow regime, offering little operational flexibility. These facilities provide only base power generation, lacking the ability to store water for periods of peak demand.[3]

RESERVOIR: A facility that has the ability to store water in reservoirs to regulate electricity generation and also accumulate energy to compensate for seasonal or even annual variations (depending on storage capacity). With the capacity to store water, and therein potential energy, reservoir dams are better able to withstand fluctuations in river flow and can be operated to provide base-load power, as well as peak-load through its ability to be shut down and started up at short notice according to the demands of the system. Given their ability to control water flows, storage reservoirs are often built as multi-purpose systems, providing additional benefits as discussed later in this section.

3 However, an upstream reservoir dam may act as storage for downstream run-of-river dams, restricting the flow during off-peak periods and releasing more water during periods of peak electricity demand.

PUMPED STORAGE: This typology of hydropower stores power as potential energy. This power often comes from surplus generation of other sources with relatively inflexible generation schedules, such as wind and solar PV. Typically, electricity from these other sources is used to pump water up to a higher reservoir during off-peak hours. Then, during peak hours, the water is released to the lower reservoir to generate electricity. *Pure* pumped storage, in which the reservoirs are not connected to a river network, is the most deployed of this technology. Its value is in the provision of energy storage, enabling peak demand to be met, assuring a guaranteed supply when in combination with other renewables, and other ancillary services to electrical grids.

Hydropower facilities installed today range in size from less than 100 kW to greater than 22 GW, with individual turbines reaching 1000 MW in capacity. Hydropower technologies are not bound by size constraints – the technology is the same regardless of the size of the project. Large-scale hydropower facilities typically require upstream water reservoirs and can impound the entire flow of a large river. Small and medium hydropower facilities can either have an upstream reservoir, or they can be installed along side a river, stream or existing water supply network, such as wastewater drainage systems. Small (and mini, micro and pico) hydropower plants are typically run-of-river schemes or implemented in existing water infrastructure.

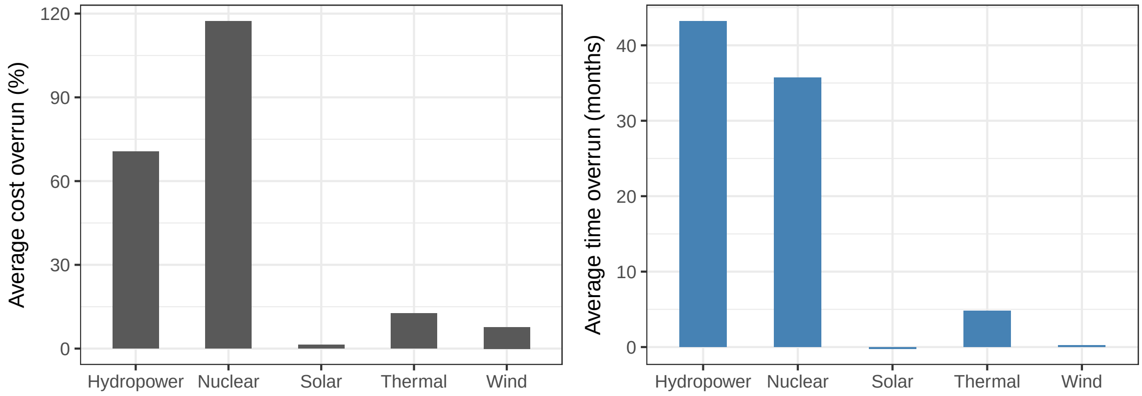
1.3.2.2 *Economics and finance of hydropower*

Several studies have analysed the levelised cost of electricity (LCOE)[4] of hydropower, showing that under good conditions, it can be as low as 3 to 5 US¢ per kWh (IRENA, 2012b, 2015b; **?**; IPCC, 2012). Civil works cost can be the largest share in the total LCOE, ranging between zero (for an existing project) to a high of 63% (IRENA, 2012b). The share of electro-mechanical equipment costs can range from a low of 17% to 50%, with typical values ranging from 21% to 31%. These costs are only referential and can vary considerable from country to country and project to project.

Similar to other capital-intensive large infrastructure projects, hydropower requires high initial investment, but has a long lifespan with very low operation costs and a relatively stable and sustained revenue stream. The public sector has traditionally been the main financier of hydropower, as these projects are major infrastructure investments (Mišic and Radujkovic, 2015). Investment is also increasingly coming from new international players, both public and private. Chinese companies, for example, are investing

4 Levelised cost of energy (LCOE) is defined as the present value (computed at a specified discount rate) of all the resource costs (planning, construction, operating, etc), divided by the present value of the energy (at a fixed price).

Figure 1.4: Average time and cost overruns for electricity infrastructure



Source: Sovacool et al. (2014b)

heavily in Africa and South America (Alves, 2013). Historically, the decision for investment in hydropower is often made on an economic basis; however, another factor that has become increasingly important in the investment decision is the non-power services that hydropower can bring to a region. For example, many hydropower projects offer an element of flood protection for the local region and the economic value lies in the value preservation and avoidance of damages (Jordan et al., 2012; Ward et al., 2013). Although it is a highly valued benefit, there is no specific contribution to return on investment for this service. Other multi-purpose benefits include drought management (Harto and Yan, 2011; Harou et al., 2010) and irrigation (Tilmant et al., 2009; Zeng et al., 2017), which typically do not offer clear and direct revenue streams to reservoir developers. Hydro projects also bring significant macroeconomic and societal benefits, such as employment opportunities, both during and after construction.

Hydropower's financial performance has been subject to criticism regarding cost and schedule overruns (Ansar et al., 2014). A study by Sovacool et al. (2014b), who assessed construction cost overruns of 401 power plant projects developed between 1936 and 2014 in 57 countries, has shown that hydropower projects can have an average cost overrun of 70% and an average time overrun of 43 months, compared to, for example, an 12% average cost overruns and 4 months average time delay for a thermal plant (see Figure 1.4). The largest risks of cost and time overruns of hydropower lie on the complexities surrounding the planning and construction phases of the dam and reservoir. For illustrative purposes, Table 1.3 on the next page shows a list of identified hydropower projects that have registered the highest mean average cost overrun according to Sovacool et al. (2014a). Reservoirs can extend to hundreds or even thousands of square kilometres, requiring detailed studies of the hydrology, geology, topography, environmental and social impacts. This increases early capital requirements, and therefore risk, as some

Table 1.3: Hydroelectric projects with the largest mean cost overrun escalation

Rank	Date	Name	Country	Cost overrun (%)
1	2006	Sardar Sarovar Dam	India	513
2	2011	Bakun Hydroelectric Project	Malaysia	417
3	2012	Three Gorges Dam	China	402
4	1978	Sayano-Shushenskaya	Russia	353
5	1979	La Grande 2	Canada	246
6	1976	Nurek	Tajikistan	200
7	1950	Vinistra	Norway	190
8	1977	Kariba Stage 2	Zambia/Zimbabwe	177
9	1981	Robert-Bourassa	Canada	143
10	1986	Chixoy	Guatemala	136
11	2009	Longtan Dam	China	113
12	1986	Guir (Raul Leoni)	Venezuela	101
13	1985	Third Power	Swaziland	100

Source: Sovacool et al. (2014a)

of the studies are undertaken before there is any certainty around project authorisation. During the construction phase, risk is generally due to cost containment from unforeseen problems. During the operational phase, hydropower's low maintenance costs and no fuel requirement mean that most capital costs have already been incurred and revenues are typically stable. However, while risks decline significantly once the plant is put into service, operational risks can include changes in long-term hydrological conditions (Babur et al., 2016) and more stringent regulatory environments (Anderson et al., 2018). Therefore, this thesis looks into how to assess hydropower under uncertainties of cost overruns based on past evidence and to depict its characteristic discrete investment profile, which is a step forward compared to other studies that consider overruns in a deterministic manner and using a linear capacity expansion approach, respectively.

1.3.3 *The role of hydropower in the electricity mix*

Hydropower has traditionally been developed to provide two services to the power system:

BASE AND PEAK LOAD POWER: Hydropower is considered to be a source of low-cost base-load power (particularly run-of-river), given that its operating cost is low compared to fossil alternatives which must incur in fuel costs. Peaking power can also be provided due to the ability of the technology (reservoir hydro) to release water at short notice to respond to immediate needs for more power on the grid. More recently, this traditional role of hydropower is evolving with the increased share of variable renewables energy sources such as solar PV and wind.

ENERGY STORAGE: Hydropower reservoirs allow to store potential energy for later use at timescales ranging from seconds, to days, to several months and even years. When fossil fuel generation or other non-hydro renewables are feeding electricity into the grid, hydropower stations can reduce their output to store water in their reservoirs. This storage can be used later to increase hydropower output and fill deficits when, for example, wind or solar sources fall.

However, due to the uncertainty of runoff, the amount of energy that a hydroelectric system can guarantee is smaller (which means that the hydroelectric availability factor[5] ~50% is lower than thermal-based alternatives ~90%). Therefore flexible thermoelectric power plants (usually fired with fuel oil and natural gas) complement hydroelectric generation, increasing the robustness of the system – what is know as a *hydrothermal* power system. Thermoelectric power plants operate synchronously with hydroelectric plants in order to increase the amount of energy the system can guarantee by increasing the energy supply of the hydroelectric system[6] and avoiding the waste of energy through spillage.

The purpose of the hydrothermal system operation (short-term) is to determine the hydraulic and thermal electricity dispatch in order to minimise the expected cost of operation, including fuel (thermal) and non-supply (deficit/importing) costs. At the same time, the expansion of the power system looks into the deployment of a generation portfolio that minimises total system costs in the long-term. Figure 1.5 on the facing page summarises the short and long-term dilemmas of the operation and expansion of a hydrothermal system.

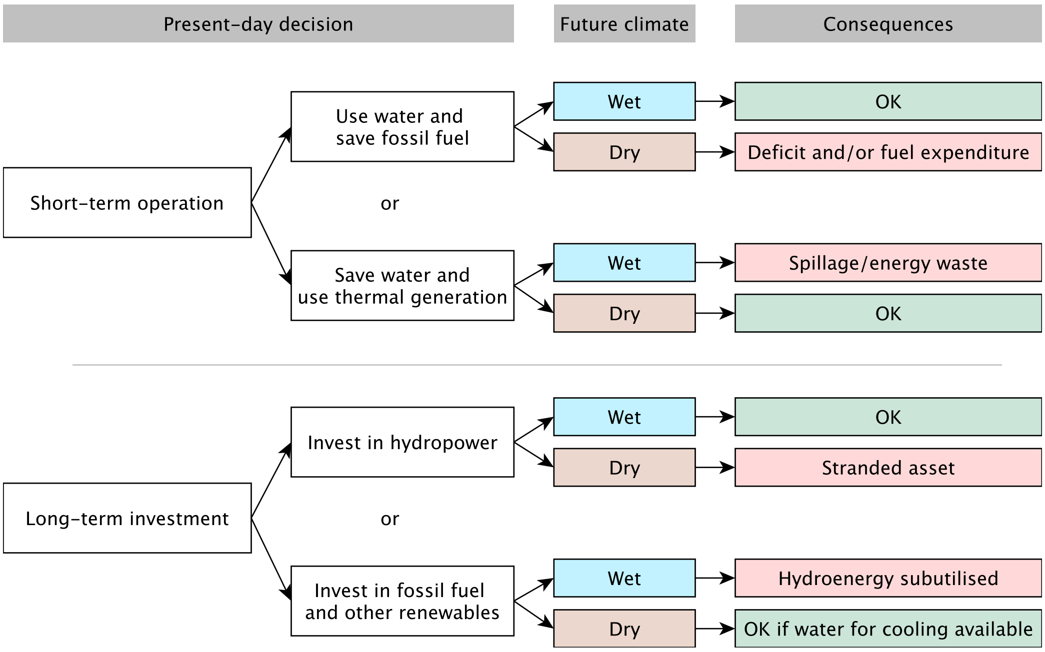
In the short-term, if the operator decides to use the water from hydropower reservoirs to generate electricity in the present, future thermal expenditures (or even power deficits) may be incurred if the hydrological conditions are not good enough to refill the reservoirs. On the other hand, if the operator decides to store water, it is necessary to use thermal generation to meet the present demand. If, in the future, the inflows are low, this decision was right, because there is water to generate hydroelectric power. However, if the inflows are high, there may be no reservoir capacity to store water and the system will waste energy through vents and spillage.

In the long term, energy authorities can decide to incentive the deployment of hydropower or thermoelectric power plants (which would traditionally be fossil fuel based) depending on the source that is expected to dominate the power system. However, these

5 Availability factor, a ratio of hydropower production over the maximum theoretical production, subject to a defined time period.

6 Not only by increasing total installed capacity, but mainly by increasing the amount of electricity generated by hydroelectric plants without the risk of non-supply. In this sense, thermal power stations work as an insurance that allows the system to deplete its reservoirs with less risk of not meeting future demand.

Figure 1.5: Operation and expansion dilemma of a hydrothermal power system



Source: adapted from Lucena (2010)

decision must be taken without enough certainty of the positive or negative changes that runoff could experience due to climate change. If the country decides to deploy hydropower extensively and this coincides with a dry water availability scenario, there is a risk of having underused or even stranded hydropower infrastructure. If on the other hand the country decides to move towards a larger share thermal-based generation, the occurrence of dry scenario might be without problems (as long as enough cooling water is available), but the occurrence of a wet scenario would mean that valuable low-cost hydroenergy resources are not being used.

This thesis will analyse the trade-offs for the power system to adapt to the occurrence of wet or dry scenarios caused by climate change. In addition, special attention will be given to how hydropower technology is represented in an energy system model, particularly on the differences among run-of-river and reservoir, and their distinctive contribution in the operation of the power system. This goes beyond studies that have represented hydropower without differentiating between run-of-river or with reservoir types (e.g. van der Zwaan et al., 2018; Teotonio et al., 2017). This will be further discussed in the literature review in Chapter 2 on page 23.

1.3.4 *The role of hydropower in climate change mitigation and adaptation*

Hydropower and climate change show a double relationship. On the one hand, as an important renewable energy resource, hydropower contributes significantly to the reduction of GHG emissions and therefor to the mitigation of global warming. On the other hand, climate change is likely to alter river discharge, impacting water availability and hydropower generation.

In terms of mitigation, hydropower is a very low GHG emission technology when compared to conventional fossil fuel plants. According to IHA, if global hydropower generation was replaced with burning coal, approximately 4 billion tonnes of additional GHG would have been emitted in 2017 (IHA, 2018), which represents about 10% of global annual GHG emissions. Although there can be some GHG emissions of decaying biomass beyond the surface of a hydropower reservoir, these values range from 3 – 4 gCO_2eq per kWh for hydropower run-of the river, and 10 – 33 gCO_2eq per kWh for hydropower with a reservoir; these values are Tenths of times lower than the emissions from traditional thermal power (~500 gCO_2eq for natural gas, ~800 gCO_2eq for oil and ~1000 gCO_2eq for coal) (WEC, 2004; Edenhofer, 2011). The World Bank conclusively produced a report entitled: "Greenhouse gases from reservoirs caused by biochemical processes" (World Bank World Bank Group, 2013), which gave concrete guidelines on how GHGs from reservoirs can be studied within the environmental impact assessment (EIA) process. The main conclusions were that the perception that reservoirs emit high levels of GHGs largely stems from older studies that were mainly conducted at sites with very unfavourable conditions. GHG emissions seem to be relatively small for an overwhelming majority of reservoirs.

In the last decade, hydropower, wind energy, and solar energy have been developed strongly, with a spectacular increment of renewable energy (IRENA, 2017). Hydropower has a timely synergy with wind and solar renewable energy sources, as wind and solar energies are intermittent and very variable, while hydropower is able to balance out variability and supply the peak load. In addition, hydropower is the only system that currently exists to store energy in a significant and effective way, in the form of pumped storage power plants, which make up 97.5% of global energy storage in the electricity networks (IRENA, 2017).

In terms of adapation, hydropower projects may also have an enabling role beyond the electricity sector, as a financing instrument for multipurpose reservoirs and as an adaptive measure regarding the impacts of climate change on water resources. The projected changes described in the Fifth Assessment Report (AR5) of IPCC include an increase in water resources at high latitudes, in tropical East Africa, and in Southeast Asia, and a decrease of water resources in many semi-arid and arid areas (e.g. the Mediterranean Basin, Western US, Southern Africa, and Northeastern Brazil) (Cisneros et al., 2014). Therefore, given the current circumstances and the need for responsible development in the contexts of a changing world and climate change, increasing water storage capacities is a major imperative (Berga, 2016). Regulated basins with large reservoir capacities are more resilient to water resource changes, less vulnerable to climate change, and act as a storage buffer against climate change. At the global level, the overall impact of climate change on existing hydropower reservoirs may be expected to be small, or even slightly positive as Turner and Galelli (2016) have shown. However, there is the possibility of substantial variations across regions and even within countries. Therefore the need to assess the impact of climate change on hydropower at the regional and national levels, and how its role both for adaptation and mitigation is affected.

1.3.5 *Socio-environmental challenges for hydropower development*

The IPCC's Special Report on Renewable Energy (SRREN) (IPCC, 2011) mentions that climate change can affect hydropower by three means:

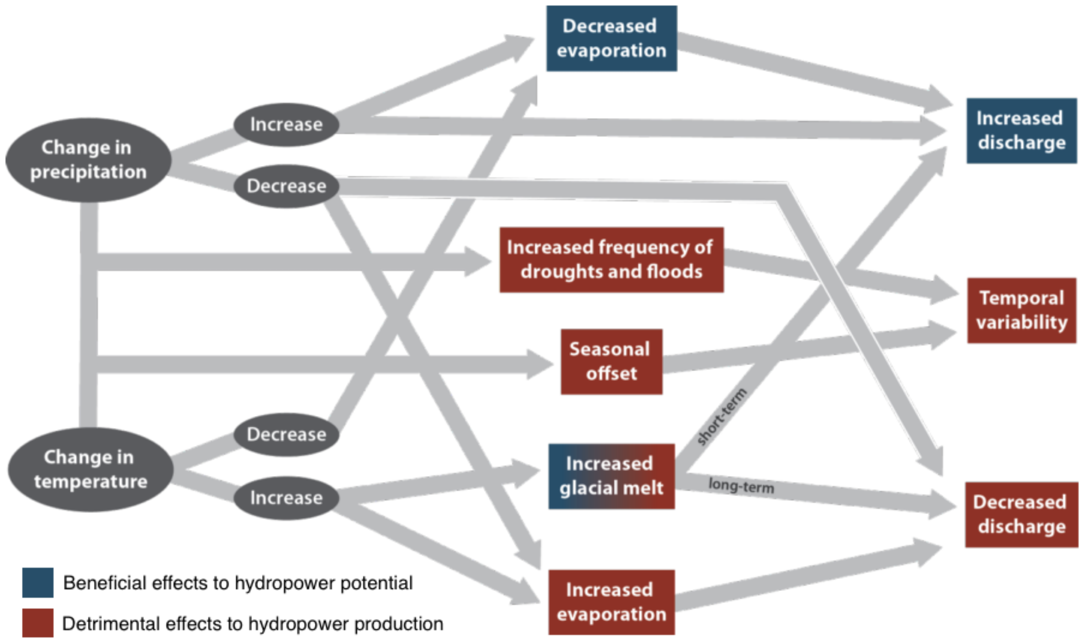
- Changes in river runoff (mean annual stream flow, shifts of seasonal flows, as well as by increased evaporation from reservoirs) due to changes in precipitation and temperature in the catchment area;
- Changes in extreme events (flood and droughts); and,
- Changes in sediment loads[7]

Blackshear et al. (2011) present a qualitative framework for modelling the future of global hydroelectric resources in the context of its vulnerability to climate change. The authors indicate that precipitation and temperature are the two most important hydro-climatic variables that will impact hydropower, as can be seen in Figure 1.6. The change in hydro-climatic conditions caused by climate change and its effect of hydropower has been studied in both isolated (e.g. Babur et al., 2016; Gaudard et al., 2013) and integrated manners with different type of mathematical tools (e.g. Kannan and Turton, 2011; Grijsen, 2014; Gernaat et al., 2017). However, most studies have only used few climate change projections and at the seasonal inter-anual level, thus missing the impacts of both high and low precipitation months. This is a gap found in the literature, which would be discussed in greater detail in the literature review in Chapter 2 on page 23and which this thesis seeks to address.

It is important to mention that water is a renewable, but fixed resource to be shared. Hydropower plays a crucial role in the energy-water nexus. On the one hand, the ver-

7 Sediment entrapment within reservoirs, which has been shown to gradually decline storage capacity and hence power production over the years (Wisser et al., 2013).

Figure 1.6: Flow chart of climate change effects on hydroelectric production.



Source: Blackshear et al. (2011)

satility of hydropower plants can be exploited to alleviate local water stresses – diverted water can be made available for other purposes such as irrigation and drinking water supply. On the other hand, hydropower can add to the stress of water resources by creating socio-environmental impacts most likely related to the impoundment of water, and the hydrological changes brought about through the construction of dams and the flooding of land downstream. However, hydropower projects are site specific and as such, each project will differ in its socio-environmental impacts, positive or negative, depending on issues such as size, geography, and the characteristics of the surrounding environment and communities (WEC, 2015a).

Hydropower's environmental impacts can be related to its land footprint caused by flooding large areas to allocate a reservoir. This is difficult to assess because there are a series of water management benefits that could outweigh the loss of land used for the reservoir, such as flood control, better irrigation and water conservation during droughts or arid seasons. A water footprint can also be caused by the loss of water through evaporation from large reservoirs. In recent studies (Bakken et al., 2016), water consumption rates have been found to be very close to zero (i.e. evaporation from the host environment before and after creation of the hydropower plant are the same). Another impact is the build-up and release of significant amounts of GHG emissions (methane) by decaying vegetation in flooded river beds. Life-cycle emissions from large reservoirs could be high from plants in tropical regions (IPCC, 2011). The construction and operation of a dam also impacts the rate of sediment transport in a river, leading to sediments becoming trapped in the dam. This affects both operation of the hydropower station (reduction of storage capacity) and the distribution of sediments and nutrients downstream. Finally, the construction of a dam has shown to fragment wildlife processes and migration patterns of fish (Anderson et al., 2018).

Social challenges are also present, especially in the development of large-scale hydropower projects that require high capital investments and include higher potential impacts on the local environment, the possible displacement of communities, and the competing demands between energy, water and land use (Delang and Toro, 2011; Ty et al., 2013; Namy, 2010). While governments generally view hydropower in a favourable light, as they are a means of reducing national emissions, boosting energy security and fostering economic development, hydropower projects can still either enjoy the local support or be met with increasing resistance. The role of governments on hydropower development is to ensure that projects meet acceptable sustainability requirements – economic, social and environmental – and that all negative impacts that may be incurred from the projects are mitigated to the bare minimum (Winemiller et al., 2016; Gracey and Verones, 2016; Lees et al., 2016). This is of prime importance to developing and emerging economies considering hydropower development, ensuring that the benefits from hydro projects are enjoyed across the country, and especially in areas where the scarce water resources are being exploited. International hydropower developments (cross-border) can also face opposition or support, depending whether the interest of the stakeholders across borders are sufficiently taken into consideration (Simpson, 2013; Douglass, 2016; Grumbine et al., 2012).

In the context of this research, energy system models inform policy makers about the conditions under which hydropower is part of the least-cost long-term development pathway of the power sector. Traditionally, if there are resources available, hydropower stands out as a technology that should be deployed largely given its low running costs and long-lived infrastructure. However environmental and socio-economic issues ultimately translate in cost and time overruns that should be taken into consideration when hydropower is represented in an energy model.

1.4 thesis outline

The thesis consists of six chapters and accompanying appendixes. The first chapter is the Introduction, in which the motivation, guiding research questions and context for this thesis have been presented.

Chapter 2 on the next page carries out a critical review of the scientific literature of climate change impact studies on energy systems and on hydropower in particular; with explanations of the different approaches and methodologies that researchers have used to assess the issue. This chapter will also include the approaches to assess uncertainty in climate change impact studies and in energy system modelling.

Chapter 3 on page 91 focuses on the proposed method to answer the research questions. This chapter will contain a detail on how to use the range of results from climate change projections as a proxy to characterise the probability space of hydropower output (Research question 1). This chapter will also present the structure and assumptions of the energy system model developed for Ecuador (Research question 2). In addition, a novel approach will be presented in this chapter detailing how to integrate risk analysis into an energy system optimisation model (Research question 3).

Chapter 4 on page 181 will present the results obtained when applying the detailed method for Ecuador's power expansion pathways by 2050. The different configurations of the power sector will be assessed under different scenarios of climate change, policy and risk. Given the use of an integrated energy system model, secondary impacts on electric and final energy demand will also be shown. The answers to the research questions will be presented in this chapter.

Chapter 5 on page 249 will frame a discussion around the results of this study according to the limitations of the applied method. Limits to generalisation of the results and the replication of the method in other latitudes will also be presented in this chapter. Areas for future research have also been detailed here.

Finally, Chapter 6 on page 271 restates the research questions and summarises the main conclusions of this thesis. The originality and contribution of the research are clearly stated as well as key insights for the policy making arena.

2

LITERATURE REVIEW

This chapter presents a literature review with the aim of describing the current state-of-the-art modelling of climate change impacts on hydropower systems. First, a background on the impacts of climate change on energy systems is provided in Section 2.1. Second, a review and discussion of different approaches for modelling the impact of climate change on water resources and hydropower generation are discussed in Section 2.2. Third, a review on uncertainty treatment in climate change impact assessments and energy system models is carried out in Section 2.3. Finally, the chapter ends with a summary in Section 2.4 with respect to the research questions of this PhD thesis framed within the gaps found in the literature.

2.1 CLIMATE CHANGE IMPACTS ON ENERGY SYSTEMS

The growing amounts of GHG emissions in the atmosphere is the major driver of global climate change (IPCC, 2007). According to the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), climate projections point out that without additional efforts to reduce GHG emissions beyond those in place today, emissions growth is expected to persist driven by growth in global population and economic activities (IPCC, 2014d). The worst scenarios result in an increase of global mean surface temperature of 3.7°C to 4.8°C compared to pre-industrial levels. To maintain the temperature in a range of 2°C well below this threshold, CO_2e concentrations should not exceed 450 ppm, however, by 2011 estimations of concentration level were already at 430 ppm (IPCC, 2014d).

Climate change, in its different directions and forms will have direct and indirect impacts on natural and human systems, including energy systems (renewable and non-renewable) that are exposed to weather conditions, thus making them vulnerable. The contributions of Group II of the IPCC for the AR5 (IPCC, 2014a), consisted in assessing the impacts, adaptation and vulnerability of natural and human systems due to climate change. According to the authors, a focus on risk assessment, is novel in this latest report, and is envisioned to support decision making in the context of climate change: *"Responding to climate-related risks involves decision-making in a changing world, with continuing uncertainty about the severity and timing of climate-change impacts and with limits to the effectiveness of adaptation."* That is why it is crucial to study how to mitigate and adapt to these new climatic conditions.

According to the Technical Guidelines for Assessing Climate Change Impacts and Adaptations of the IPCC (Carter et al., 1994), there are four methods to assess impacts of climate change: i) experimentation, ii) impact projections, iii) empirical analogue studies, and iv) expert judgment. Relevant to this literature review are *impact projections*, in which mathematical models are extrapolated into the future. This method is the only one that allows a formal and objective analysis of the mentioned issue of climate change impact on energy systems.

In a scenario with higher ambient temperatures, climate models show variations (in magnitude, frequency, geographic regions) of hydro-meteorological and other climate parameters. Table 2.1 on the facing page presents climate change impacts on the energy sector, as has been presented by the US Department of Energy (DOE, 2015). Renewable energy, namely hydropower, wind energy, solar energy and biomass energy, is specially affected by climate change, since its *renewability* depends on the weather and long-term climate trends.

Notice that in Table 2.1 on the next page not only impacts on renewable energy systems that directly depend on climate are included, but non-renewable energy systems and transport infrastructure that may also suffer consequences. For example, alterations in river flow can impact cooling water needs for thermoelectric and nuclear power plants (Liu et al., 2017); the temperature and humidity of air has an effect on the performance of natural gas turbines (Schaeffer et al., 2009); and extreme climate events such as storms and hurricanes can affect oil production in off-shore platforms (Wilbanks et al., 2008).

Even though compared to hydropower, wind farms, solar facilities and biomass generation systems are likely to be more vulnerable to potentially negative impacts from climate change (variations in wind, temperature, precipitation and irradiance); these technologies have short life-spans (<20 years), which make them more adaptable in the long-term. Analysing impacts on short life-span technologies would imply in assuming that the existing facilities would be replaced over time by similar technologies at

Table 2.1: Potential effects of climate change on the energy sector

Energy sector	Climate projection	Potential implication
Oil and gas exploration and production	Decreasing water availability, increasing frequency of intense hurricanes and sea level rise.	Impacts on drilling, production, and refining.
Fuel transport	Reduction in river levels, increasing intensity and frequency of flooding.	Disruption of rail and barge transport of crude oil, etc.
Thermoelectric power generation	Increasing air and water temperatures, decreasing water availability.	Reduction in plant efficiencies and exceeding thermal discharge limits.
Hydropower	Increasing temperatures and evaporative losses, changes in precipitation and decreasing snowpack, increasing intensity and frequency of flooding	Reduction in available generation capacity and changes in operations. Increased risk of physical damage.
Bioenergy and biofuel production	Increasing air temperatures and decreasing water availability	Increased irrigation demand and risk of crop damage.
Wind energy	Potential variation in wind patterns	Uncertain impact on resource potential.
Solar energy	Increasing air temperatures and decreasing water availability	Reduction in concentrated solar power (CSP).
Electric grid	Increasing air temperatures, more frequent and severe wildfires and intense hurricanes	Reduction in transmission efficiency and risk of physical damage.
Energy demand	Increasing air temperatures Increasing magnitude and frequency of extreme heat events	Increased electricity demand for cooling; decreased fuel oil and natural gas demand for heating.

Source: Adapted from DOE (2015)

the same location, which might not be the case. Thus, for some technologies for which there is still some room for advances or relocation, climate impacts can be overestimated. Although, other kind of studies could be carried out that also look into the impacts of climate change on short-lived renewable energy generation technologies, e.g. running an energy system optimisation model with different climate change influenced wind/solar trajectories to assess what the impact on the system is. So, while the climate impacts on short life-span technologies are less relevant in terms of causing stranded/less than optimal investments, they can be meaningful in terms of what the least cost system should look like, due to varying electricity generation trends in the short-term. In any case, although long-term energy planning can assess the operation of the energy system at the inter-annual level (according to the time slice resolution used), its primary focus is in assessing investments for capacity of energy conversion infrastructure, i.e. installed electricity capacity expansion, when it comes to the power sector. Thus for the focus of this thesis, the varying trends of energy production of short-lived renewable energy technology due to climate change is of less importance, given its flexibility to change locations, as explained previously.

In comparison, the decision to build a hydropower station entails not only in high capital and environmental costs but also in a stationary structure with a longer physical and economic life-span (>75 years). Because global climate change should happen in the mid to long-term, climate impacts analyses must assume that a major share of the current energy system (and even the energy facilities under construction or planned to be built in the next few years) will be still operating when the new climate conditions occur. This is a plausible assumption for long lived hydropower plants, which needs to be assessed with the aid of long-term climate and energy system models. The risk of long-lived assets becoming stranded due to the lack of water resources to operate them leads to non-optimal investment decisions and in reality would require duplication of installed capacity and increase possibilities of black out. This is the reason why hydropower has been chosen as one of the electricity generation technologies that is most vulnerable to climate change impacts and is the focus of this thesis.

The section will give an overview of the overall impacts of climate change on energy supply and energy demand in general. Non-hydropower and hydropower electricity generation technologies will be described in terms of their vulnerability to climate change induced meteorological variations and the challenges to assess them with climate projections. For a broader review of trends and gaps in studies of climate change impacts on energy systems refer to Schaeffer et al. (2012) and Cronin et al. (2018).

2.1.1 *Impacts on energy supply (except hydropower)*

2.1.1.1 *Wind power*

The availability and reliability of wind power depend on weather and climate conditions. Pryor and Barthelmie (2010) present a review of studies focused on the impact of climate change on wind power generation, analysing the mechanisms through which climate change can influence wind resources and its operation conditions, as well as the tools that have been used for these purposes and the uncertainties related to them. The main mechanisms by which global climate change impacts wind energy endowments are: i) shifts in the geographical distribution, and ii) the variability of wind speed patterns. The first implies different impacts on wind resources across regions (Zeyringer et al., 2018). As for the second, wind speed patterns (and their variability) define the economic feasibility of exploiting wind resources and the reliability of electricity production once the capacity is installed (Hdidouan and Staffell, 2017).[1]

However, future climate projections have serious limitations in reproducing wind speeds and their frequency distributions or directional changes (Pryor and Barthelmie, 2010).[2] Wind resources may have their beginnings in global circulation but are primarily shaped by their site (Musgrove, 2009). The IPCC's Special Report on Renewable on Renewable Energy (SRREN) (Wiser et al., 2011), concludes that research to date suggests that impacts are unlikely to be of a magnitude that will greatly impact the global potential of wind energy deployment. This conclusion has been replicated by studies primarily focusing on changing wind speeds that reach high level regional considerations on the climate change impact on energy potentials, such as the studies for the UK (Hdidouan and Staffell, 2017), South Korea (Oh et al., 2012), Brazil (De Lucena et al., 2010b), Northern Europe (Lavergne et al., 2014) and at the global scale (Karnauskas et al., 2018). Though potentially significant, the findings of these studies rely on climate models with relatively low spatial resolution, which could make it difficult to draw meaningful conclusions.

1 Considering that wind power generation is a function of the cube of the wind speed, drops in wind speed correspond to potential reductions in wind power generation of a larger order than the variation of the wind resource.

2 Three characteristics of climate models render them imperfect tools for assessing wind energy potential: i) climate models have coarse horizontal resolution, ii) wind turbines operate as heights typically 40–120 m above the surface, whereas the vertical grid structure of climate models is such that wind information is available only at a height of 10 m and on standard pressure levels, and iii) climate models provide monthly mean fields, whereas winds fluctuate at much higher frequencies (Karnauskas et al., 2018).

2.1.1.2 *Solar energy*

Climate change can affect solar energy resources by changing atmospheric water vapour content, cloudiness and cloud characteristics, which in turn affects atmospheric transmissivity (Edenhofer, 2011). This can have impacts on the amount of irradiance that reaches photovoltaic (PV) and concentrated solar power (CSP) facilities. Higher temperatures and surface wind velocity can impact PV panel efficiency (Flowers et al., 2016). Higher temperatures and decreasing water availability can reduce thermal plant efficiencies and increase risk of exceeding thermal discharge limits of CSP facilities (Ebinger and Vergara, 2011). As impacts of climate change on the detailed atmospheric variables may have different trends around the world, so would solar energy resources, have positive impacts in terms of increase in solar irradiance in some situations (e.g., reported increase in solar resource in the UK, Burnett et al., 2014), negative impacts in terms of decrease in solar radiation (e.g., reported decrease trend in incoming solar radiation in Canada, Cutforth and Judiesch, 2007) or even negligible changes (e.g., low probability of significant changes in southern Africa, Fant et al., 2016).

According to the SRREN report (Arvizu et al., 2011), the compilation of studies reviewed using climate models and anthropogenic forcing found that the pattern of variation of monthly mean global solar irradiance does not exceed 1% over some regions of the globe, though it varies according to model used. However, there are studies that project variations at a regional scale that could be relevant, such as Jerez et al. (2015), that assess the impact of climate on solar PV production at the scale of the European regional electric grids considering a future scenario with a strong penetration of PV installations. Results indicate that the alteration of solar PV supply by the end of this century compared with the estimations made under current climate conditions should be in the range (-14% – +2%), with the largest decreases in Northern countries. Uncertainties still remain in assessments of climate change on solar resource, due for instance to indirect effects of natural and anthropogenic aerosols and to land-use changes, both features being currently poorly represented or totally ignored in climate models (Gaetani et al., 2014).

2.1.1.3 *Biomass and liquid biofuels*

The production of biomass and biofuels for energy production may also be impacted by climate change. Increasing air temperatures and higher CO_2 levels can derive in extended growing seasons due to improved photosynthesis, which in coincidence with decreasing water availability can cause an increase in irrigation demand and risk of crop damage from extreme heat events (Schaeffer et al., 2012). Besides changes in precipitation and water regime, increases in temperature levels leads to higher evapotranspiration rates.[3] Sea level rise and increasing intensity and frequency of flooding can also harm not only biomass for energy production, but threat food production systems and food security itself (Porter et al., 2014). These processes directly affect many key factors of agriculture, like crop yield, agricultural distribution zones, incidence of pests and the availability of lands suitable for growing some energy crops.

The literature that assesses the impacts of climate change on crops used for biofuels, mostly focus on ethanol production (sugarcane and maize) and biodiesel (soybeans, rapeseeds, sunflower seeds, castor beans, etc.). De Lucena et al. (2009) used long-term climate projection scenarios to assess the possible impacts of biofuel production in Brazil. The results of the study state that climate change will not significantly affect negatively the production of sugarcane ethanol in Brazil, given sugarcanes capacity to withstand high temperatures as long as enough soil moisture is provided. However, the production of biodiesel in the country could be affected negatively by climate change, mainly in the northeast, with a shift of suitable growing zones for oilseed crops to the southern region.

Srivastava et al. (2018) presents an estimate of the effects of climate variables on potential maize productivity and an assessment of the most limiting climatic drivers in the future climate scenarios for maize production in central Ghana. Results show a substantial increase in the average maize yield in all projected future climate scenarios analysed by 2080 compared to the baseline, due to the beneficial effect of CO_2 on the radiation use efficiency of the crop combined with only moderate changes in amount of rainfall and incoming radiation during the growing cycle of maize. For Ghana, the study demonstrates that today and under future clime conditions water would not be the most limiting factor during the maize growth period, whereas, temperature (through shortening of the maize growing cycle), nutrients and solar radiation may remain the limiting factor for maize production in the region.

Piao et al. (2010) assessed the impacts of climate change on water resources and agriculture in China, however they conclude that notwithstanding the clear warming that has occurred in China in recent decades, current understanding does not allow a clear assessment of the impact of anthropogenic climate change on China's water resources and agriculture. According to these authors, to reach a more definitive conclusion, future work must improve regional climate simulations – especially of precipitation.

3 Evapotranspiration (ET) is the sum of evaporation and plant transpiration from the Earth's land and ocean surface to the atmosphere. Evaporation accounts for the movement of water to the air from sources such as the soil, canopy interception, and waterbodies. Transpiration accounts for the movement of water within a plant and the subsequent loss of water as vapour through stomata in its leaves. Evapotranspiration is an important part of the water cycle.

The mentioned studies however mostly assess variations in climate patterns and temperature but leave out the effects of drought and flooding. Particularly drought can have a critical impact for biomass production and can also compete or collide with hydropower development plans, as the study of Shadman et al. (2016), in which a discussion on drought effects and energy security in the ASEAN-6 countries was developed.

Climate change could also present a threat for the availability of woody biomass used for cooking and heating in low-income households in developing countries. These could be impacted by desertification or *savanisation* of local biomes, which would restrict access to traditional energy in communities that depend on them. These communities would not only face a lower availability of energy, but also an increase in time and effort needed for fuelwood collection. In this sense, improved access to modern energy sources should be regarded as an adaptation strategy to increasing low-income community well-being and their climate resilience (Lauri et al., 2014).

2.1.1.4 *Thermal power plants*

Climate change can impact the availability of cooling water in terms of quantity and temperature and therefore impact the efficiency and maximum power output of thermoelectric power plants (DOE, 2015; Ebinger and Vergara, 2011).[4] The impacts derive from heating and cooling needs of both the Rankine (steam turbine) and Brayton (gas turbine) thermodynamic cycles, which vary according to average ambient conditions such as temperature, pressure, and humidity and water availability. Overall generation efficiency of thermoelectric plants can be reduced due to non-planned interruptions caused by heat waves or droughts (see Pechan and Eisenack, 2014; Rübbelke and Vögele, 2011; Kopytko and Perkins, 2011).

The effects of change in ambient temperature and humidity on the electricity efficiency of thermoelectric plants can be relatively small, however the impact depends on the share of thermoelectricity in the power system. Based on analysis of both plant-specific data and panel data for a set of European countries, Linnerud et al. (2011) conclude that a rise in ambient temperature of 1 °C will reduce electricity output by 0.4 – 0.7% at low temperatures and by about 2.3% at high temperatures. A modest variation in ambient temperature may represent a significant drop in energy supply in regions such as the US and Europe where most of electricity is generated from nuclear and fossil fuels thermal power plants (EIA, 2018b; Eurostat, 2013). The study by Sathaye et al. (2012), which was performed for California, showed that natural gas-fired power plants

4 "Thermoelectric" generally refers to power plants that use an internal combustion engine, or a steam or gas turbine to generate electricity. Examples of thermoelectric power plant fuel sources include coal, natural gas, oil, nuclear, biomass, geothermal, and concentrated solar power.

across the state could lose, on average, 4.5% peak capacity by the end of the century under a high emissions scenario. Klimenko et al. (2018), who studied the vulnerability of Russia's power sector to climate change, state that the power drop of steam turbines is about 0.2 – 0.3% and 0.4 – 0.6% per 1 °C for fossil thermal and nuclear power plants, respectively. In comparison, Schaeffer et al. (2009) concluded that thermoelectricity is robust to projected climate variations (temperature and humidity), however their study was performed for the Brazilian context which has large shares of hydropower.

Water availability is an issue at the regional scale, which means that some areas would experience a significant increase in water supply, while other regions would face the opposite (Cisneros et al., 2014). The significant amounts of water that are needed to cool thermal power facilities render them vulnerable to fluctuations in water supply. In the United States, for example, each kWh of electricity generated via steam cycle requires around between 90 – 100 litres of water (Wilbanks et al., 2008).[5]

The study of Bogmans et al. (2017), goes beyond assessing the impacts of climate change and looks into the adaptation of thermal power plants from an operator/investor's point of view, with two case studies – a coal power plant in the US and a nuclear power plant in France. The main results emerging from this study are that net losses from climate change are small, averaging at approximately 1% of net operating profits, which reflects the remarkable flexibility of current power plant technology to adjust to adverse day-to-day changes in ambient conditions during spring, fall and winter. The author argues that while climate change scenarios indicate a substantial deterioration of ambient conditions, the literature has failed to acknowledge, that thermal power plants essentially embody a flexible type of technology, which partly shields operators from these effects.

2.1.1.5 *Oil and natural gas production, infrastructure for transmission and distribution of energy*

Although climate change does not impact the actual amount of existing oil and natural gas resources, it can affect the knowledge about the availability of these resources and the access to them (DOE, 2013, 2015). In other words, new climate conditions may not impact fossil fuel resources, but could impact reserve estimates. For instance, ice-free summers can increase the length of drilling seasons in the Arctic, which can affect the rate at which new fields can be developed (Harsem et al., 2011). The infrastructure for production and transport of energy, such as transmission lines, oil production rigs and

5 Weighted average that captures total thermoelectric water withdrawals and generation for both once-through (O-T) and recirculating close-cycle (CC) cooling systems.

pipelines can also be affected by climate change by means of possible and more frequent extreme weather events (Wilbanks et al., 2008; DOE, 2013, 2015).

Oil and gas transmission systems (pipelines) can be affected by factors such as mud flows, floods, landslides, permafrost thawing and other extreme meteorological events as well as by hazards of geological nature, such as earthquakes, rockslides, etc. For example, thawing permafrost would alter the foundations of Alaska's infrastructure, and it can increase vulnerability of riverbanks and coastlines to erosion, which can destroy barge landing sites and disrupt crude oil shipments (Dell et al., 2014). Decrease in precipitation and longer dry spells may lead to more frequent droughts that will increase demand and competition for water and include withdrawals for critical operations such as oil refining operations and unconventional oil and gas production (DOE, 2013).

Electricity transmission lines are vulnerable to extreme winds and ice loads, lightning strikes, landslides, and flooding. Sathaye et al. (2012) studied impacts on transmission and distribution lines, as well as on substation/transformer capacity in California, and concluded on a positive relationship between warmer summers and system losses, which mainly has impact in peak load operation conditions of the system. The study of Lise and van der Laan (2015) assess investment needs for climate change adaptation measurers of electricity power plants in the EU. The authors state that electricity grids are the most sensitive to climate changes, with high sensitivities for air temperature (reduction in current carrying capacity or thermal ratings, and sagging lines) and increased storm damage.

The most recent study of Forzieri et al. (2018), assesses escalating impacts of climate extremes on critical infrastructures in Europe. Among over ten technologies assessed for the energy sector, gas pipelines and electricity distribution/transmission appear to have the highest sensitivity to climate change impacts, characterised by their risk to wildfires and windstorms. Followed by hydropower infrastructure, that has high vulnerability both to extreme events and to changes in hydrological patterns, specially in Mediterranean countries.

2.1.2 *Impacts on energy demand*

Final energy demand can be affected by climate change. Auffhammer and Mansur (2014) present a review of studies related to the impact of climate change on energy demand. The authors state that possible effects of climate change on energy demand include:

- Decreases in the amount of energy consumed in residential, commercial, and industrial buildings for space heating and increases for space cooling;
- Decreases in energy used directly in certain processes such as residential, commercial, and industrial water heating, and increases in energy used for residential and commercial refrigeration and industrial process cooling (e.g., in thermal power plants or steel mills);
- Increases in energy used to supply other resources for climate-sensitive processes, such as pumping water for irrigated agriculture and municipal uses;
- Changes in the balance of energy use among delivery forms and fuel types, (e.g. between electricity used for air conditioning and natural gas used for heating); and
- Changes in energy consumption in key climate-sensitive sectors of the economy, such as transportation, construction, agriculture, and others.

Temperature variations can affect mostly energy demand for cooling or heating spaces (Ebinger and Vergara, 2011). However, studies of the effects of climate conditions on energy demand are not restricting to climate change. Long before the concerns of climate change, air conditioning and refrigeration models have been used to assess the effect of climate variables on final energy service demand. This literature review will not focus on the extensive literature on climate space modelling regarding climate variations, but it seeks to identify relevant studies that focus on climate change and energy demand variations.

Most studies seeking to quantify the impact of climate change on demand have focused in some type of regression analysis between energy demand and climate variables. Parkinson and Djilali (2015) and Sathaye et al. (2011), use a multivariate regression analysis to assess how demand has changed with temperature increase in British Columbia and California, respectively. According to Isaac and van Vuuren (2009), in a business-as-usual scenario, global energy demand for heating is projected to increase until 2030 and then stabilise. In contrast, energy demand for air conditioning is projected to increase rapidly over the period to 2100, mostly driven by income growth. The International Energy Agency (IEA), states that if left unchecked, energy demand from air conditioners will more than triple by 2050, equal to China's electricity demand today (IEA, 2018). Given that the scope of this thesis is in a developing country, it must be mentioned the difficulties of assessing how temperature variations affect user energy demand. Applying traditional econometric methods in developing countries comes with difficulties given the considerable levels of suppressed energy demand and structural gaps that cannot be considered properly in econometric analysis, e.g. subsidies that distort the relationship between energy demand and prices (Debnath and Mourshed, 2018).

In the agricultural sector a warmer climate might lead to a rising demand for water and irrigation, and therefore increase the use of energy (either natural gas or electricity) for pumping. Current loss and degradation of critical agricultural soil and water assets due to increasing extremes in precipitation will continue to challenge both rain-fed and irrigated agriculture unless innovative conservation methods are implemented (Hatfield et al., 2014). The demand for cooling of livestock and poultry facilities would similarly be expected to increase in a warmer climate, and heating needs in cattle barns and chicken houses would likely fall (Wilbanks et al., 2008). The temperature differences that are bridged in industrial processes through cooling systems are often much larger than outdoor temperature fluctuations. Many continuous processes operate at relatively stable surrounding temperatures and thus have a relatively stable demand. However, little information exists on the impact of climate change on energy use in industry, as Auffhammer and Mansur have indicated.

In addition to the residential, industrial and agricultural sector, there have not been many studies found regarding the impact of climate change on transport sector energy consumption. Studies rather focus on the impact of the transport sector on climate change Chapman (2007). However, the study of Roujol and Joumard (2009) found a positive relationship between ambient temperature and fuel consumption in vehicles. Warmer temperatures will incentive higher use of air conditioning, which reduces energy efficiency of vehicles. Wilbanks et al. (2008) estimate that the efficiency of a vehicle is reduced by 12% when using air conditioning at high-way speeds.

The aforementioned studies mostly assess one particular energy source or technology. It is not generally contemplated a formal analysis of the impacts of climate change in the energy sector in an integrated manner considering the interactions among individual energy supplying and consuming sectors. Beyond this, it is to be remembered that the energy sector is integrated to other economic sectors. In addition to the technical aspects, socio-economic factors and national development policies have a great influence on the planning and operation of energy systems. Therefore, the greatest challenge in the assessment of the impacts of climate change on energy systems is to do it in an integrated fashion, as to understand the complex interactions within the energy sector itself, as well as with other sectors of the economy.

As discussed in this section, climate change impacts could affect non-hydropower electricity generation technologies, as well as other energy infrastructure (and even other types of infrastructure at large). Although all these impacts for different infrastructure could be factored in an integrated analysis, this thesis will focus only on the impacts on hydropower, given the importance that this technology has for the case study country, i.e. Ecuador. In this sense, focus of analysis will be directed by the research questions and the importance of the analysis of hydropower for the case study in question. Limitations to this approach will be discussed further in Chapter 5 on page 249.

2.2 CLIMATE CHANGE IMPACTS ON HYDROPOWER

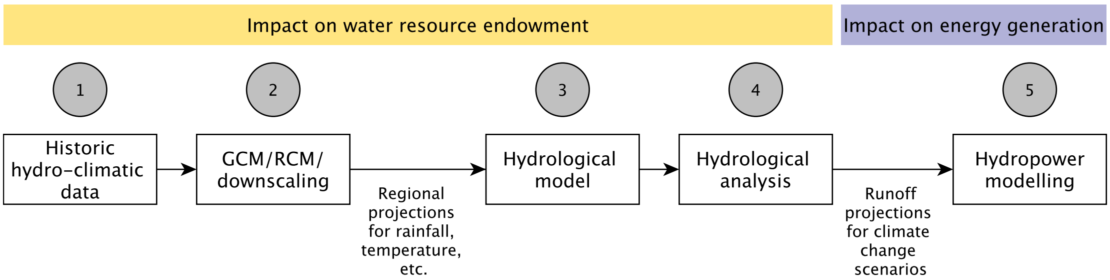
Different tools and models have been used when assessing the impact of climate change on hydropower, influenced by the characteristics of the hydropower system and the overall energy mix. However, the standard approach found in the literature (Arnell, 1992; Gosling et al., 2011; Cisneros et al., 2014; Hay et al., 2002) tends to follow the five steps shown in Figure 2.1 on the next page: i) determination of hydrological model parameters for the studied basin, using historic hydro-climatic data, ii) obtaining future projections of the hydrological parameters based on climate projections of Global and/or Regional Circulation Models (GCM, RCM), iii) development of a calibrated hydrological model and simulation of the hydrological characteristics of the river, iv) analysis of model simulations for hydrological characteristics in present and future conditions under the disturbed climatic conditions according to climate change scenarios, and v) hydropower modelling to assess impact on electricity generation. Steps one to four devote to first assess the impact of climate change on water resource endowment, followed by an assessment on energy generation. Approaches to assess each of these steps will be detailed in the following subsections.

It is important to emphasize that at each stage of the methodology presented here and illustrated by Figure 2.1 on the following page, uncertainties are added to the modeling, generating a chain of cumulative uncertainties. At each stage, also, new parameters of each stage of the modeling are added. It is proposed, initially, to keep them constant throughout the analysis so that a static evaluation can be made (or *ceteris paribus*), where the only variant factors are the climatic conditions. Limitations of this approach will be discussed in Chapter 5 on page 249.

2.2.1 *Impacts on water resource endowment*

The broadest work on climate change impacts on water resources and the implication for various sectors is the IPCC Technical Report on Climate Change and Freshwater

Figure 2.1: Standard approach used in studies to assess climate change impacts on hydropower systems



Resources (Cisneros et al., 2014). According to this report, there is strong evidence from historic observations and climatic projections that hydrological resources are vulnerable and can be strongly impacted by climate change. This would generate a broad range of consequences for ecological and human systems. Some of the main conclusions of this report regarding the key risks at the global scale that have medium to high evidence and agreement are:

- Freshwater-related risks of climate change increase significantly with increasing GHG concentrations.
- Climate change is projected to reduce renewable surface water and groundwater resources significantly in most dry subtropical regions.
- So far there are no widespread observations of changes in flood magnitude and frequency due to anthropogenic climate change, but projections imply variations in the frequency of floods.
- Climate change is likely to increase the frequency of meteorological droughts (less rainfall) and agricultural droughts (less soil moisture) in presently dry regions by the end of the 21st century.
- Climate change negatively impacts freshwater ecosystems by changing streamflow and water quality.
- In regions with snowfall, climate change has altered observed streamflow seasonality, and increasing alterations due to climate change are projected.
- There is little or no observational evidence yet that soil erosion and sediment loads have been altered significantly due to changing climate.

A detrimental aspect of the increment of GHG in the atmosphere is that it increases the uncertainty of an already uncertain hydrological cycle (Loaiciga et al., 1996). Climate change can impact water resources in terms of its annual mean availability and seasonal variability (Kundzewicz et al., 2007). Variations in river flow and lake volume related to climate change depend on variations in volume, intensity and moment of precipitation (Chiew, 2010). It also depends on evapotranspiration, which itself is function of temperature, insolation, atmospheric humidity and wind speed. Hydrographic basins respond differently to hydroclimatic variables depending on their physiographic and hydrogeological characteristics, and on the amount of water stored on the surface and underground (Green et al., 2011).

2.2.1.1 *Climate data*

Studies of the effects of increasing GHG concentrations in the atmosphere are generally based on Global Circulation Models (GCM). GCMs are biophysical models, which consist of three-dimensional mathematical representations of the atmosphere based on the physical laws that govern atmospheric physics (Taylor et al., 2012). These models are the most sophisticated tools available for simulation of the current global climate and future climate scenario projections. Their formulation usually takes into account the behaviour and interaction of flow systems in the biosphere, hydrosphere, cryosphere, atmosphere and geosphere in the climate system (Green et al., 2011).

The impact of climate change on water resources has been the focus of several studies, being one of the impacts that has received the largest amount of attention in international literature. This attention has probably originated from the concern on the representability of the hydrological cycle from GCM results. The first GCMs were developed in the 1970s and 1980s (US NSA, 1977; Nemec and Schaake, 1982), and since then there has been considerable growth in knowledge of climate processes. Over the last decades, the spatial resolution of GCMs has increased and the dominant terrestrial processes that affect large-scale climate are now included in current climate models, i.e. temperature, wind, humidity, precipitation, etc.

The ability of any particular GCM to reproduce present-day mean climate and its historical characteristics with respectable realism and good overall performance in comparison with the other models are presumed to indicate that it can be used to project credible future climates (i.e., up to the 2080s). The IPCC (2007) states, *"There is considerable confidence that climate models provide credible quantitative estimates of future climate change, particularly at continental scales and above. This confidence comes from the foundation of the models in accepted physical principles and from their ability to reproduce observed features of current climate and past climate changes. Confidence in model estimates is higher for some climate variables (e.g., temperature) than for others (e.g., precipitation)."*

The representation of important variables for the hydrological cycle, such as precipitation, evapotranspiration and thereof runoff, is a challenge for GCMs. In the one hand, precipitation is not well simulated, given that it happens in a smaller scale than that of a GCMs' grid (Xu, 1999). In addition, hydrological variables such as percolation and infiltration,[6] which are a function of specific local characteristics, are not incorporated into global models. Evapotranspiration, on the other hand, is not well represented because it happens in the so-called "GCM frontier" – the interface between the atmosphere and land surface (Loaiciga et al., 1996). Although there are complexities for GCMs to properly represent the hydrological cycle, this has not stopped GCMs to become the starting point of many studies that assess the impact of climate change on water resources. To the extent that these models seek to relate chemical changes in the atmosphere (GHG concentration) with large scale climatic variables, it is necessary to adopt concentration/emission scenarios of these gases in the atmosphere. According to Kundzewicz et al. (2018), there are two broadly applied scenario approaches: one based on the IPCC Special Report on Emission Scenarios – SRES (Nakicenovic and Swart, 2000) and a more recent one, based on the concept of IPCC Representative Concentration Pathways (RCPs) (Moss et al., 2010; Taylor et al., 2012).

The SRES scenarios are based on four qualitative storylines called "families": A1, A2, B1, and B2; as has been detailed in Table 2.3 on the facing page. A set of scenarios consisting of six scenario groups were drawn from the four families: one group each in A2, B1, B2, and three groups within the A1 family (A1FI, A1B, and A1T). For each storyline several different scenarios were developed using different modelling approaches to examine the range of outcomes arising from a range of models that use similar assumptions about driving forces (i.e. GDP and population). Altogether 40 SRES scenarios were developed by six modelling teams, which are equally valid with no assigned probabilities of occurrence.

A number of comprehensive 'model inter-comparison projects' (MIP) were established in the 1990s by the World Climate Research Programme (WCRP) to undertake controlled conditions for GCM evaluation (Taylor et al., 2012). Coordinated experiments, in which many climate models (multi-model ensemble) run a set of scenarios, have become the *de facto* standard to produce climate projections. Those multi-model ensembles sample uncertainties in emission scenarios and provide a basis to estimate projection uncertainties. The Coupled Model Inter-comparison Project Phase 5 (CMIP5) (Moss et al., 2010; Taylor et al., 2012), coordinated by the WCRP in support of the IPCC AR5, is the most

6 Infiltration is defined as the downward entry of water into the soil or rock surface and percolation is the flow of water through soil and porous or fractured rock. In hydrologic modelling, these two processes are usually modelled separately.

Table 2.3: Overview of the IPCC Special Report on Emission Scenarios (SRES)

SRES	Description
A1	Rapid economic growth, moderate population increase, high technological innovation, global convergence of living standards (A1B: Balanced, AFI: Fossil-intensive, AT: Non-fossil)
A2	Moderate economic growth, very high population increase, focus on self-reliance and local identity
B1	Moderate economic growth, move toward service and information economy, focus on environmental sustainability, global convergence
B2	Slow economic growth, low population increase, focus on environmental sustainability, regional solutions to environmental issues

Source: Nakicenovic and Swart (2000)

recent of these activities, and builds on the CMIP3, which was used to produce the emission scenarios of the IPCC SRES report (A1, A2, B1, B2) (Meehl et al., 2007). The efforts for CMIP5 have been enormous, with a larger number of more complex models run at a higher resolution with more complete representation of external forcings and more types of scenarios. The CMIP5 uses the new Representative Concentration Pathways (RCPs) (van Vuuren et al., 2011), a set of four new pathways that span the range until year 2100 radiative forcing values,[7] i.e. from 2.6 to 8.5 W/m^2; as has been detailed in Table 2.4 on the next page. The four selected RCPs were considered to be representative of the literature and included one mitigation scenario leading to a very low forcing level (RCP2.6), two medium stabilisation scenarios (RCP4.5/RCP6) and one very high baseline emission scenario (RCP8.5). For the CMIP5, the four RCPs have been formulated based on a range of projections of future population growth, technological development, and societal response.

Knutti and Sedláček (2012), who assess the robustness and uncertainties in the new CMIP5 climate model projections argue that although models have improved, representing more atmospheric processes in detail and at the regional level, the convergence among climate models will remain slow. However, the uncertainties should not stop decisions being made. These models are still the only credible tools currently available to simulate the physical processes that determine global climate and used as a base for assessing climate change impacts on natural and human systems. Figure 2.2 on the following page presents the difference between SRES and RCP scenarios for global mean temperature increase as assessed by Knutti and Sedláček. There is a large spread

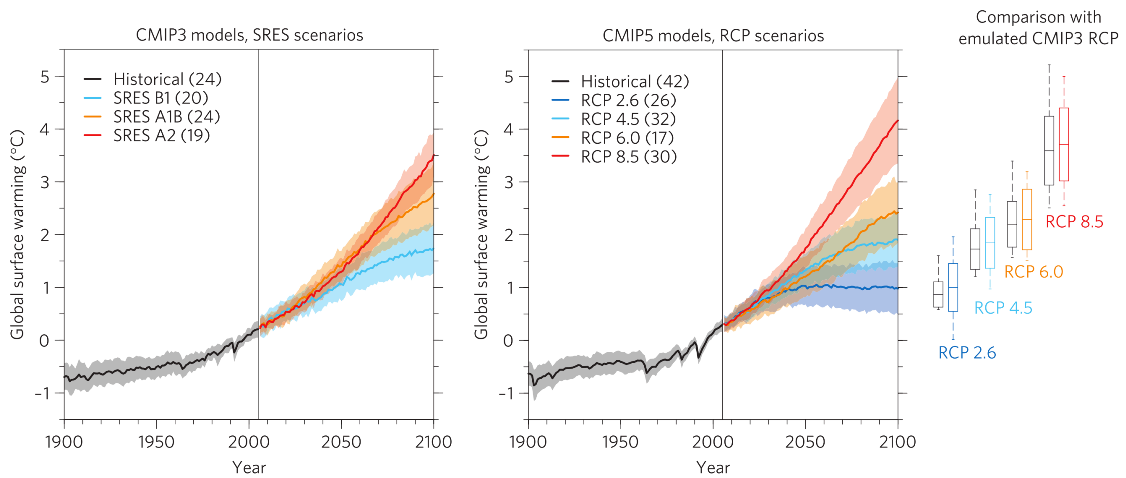
7 Radiative forcing or climate forcing is the difference between insolation (sunlight) absorbed by the Earth and energy radiated back to space (Baede, 2010). The influences that cause changes to the Earth's climate system altering Earth's radiative equilibrium, forcing temperatures to rise or fall, are called climate forcings. Positive radiative forcing means Earth receives more incoming energy from sunlight than it radiates to space. This net gain of energy will cause warming. Conversely, negative radiative forcing means that Earth loses more energy to space than it receives from the sun, which produces cooling.

Table 2.4: Overview of Representative Concentration Pathways (RCPs)

RCP	Description
RCP2.6	Peak in radiative forcing at ~3 W/m^2 (~490 ppm CO_2 e) before 2100 and then decline (the selected pathway declines to 2.6 W/m^2 by 2100).
RCP4.5	Stabilisation without overshoot pathway to 4.5 W/m^2 (~650 ppm CO_2 e) at stabilisation after 2100
RCP6.0	Stabilisation without overshoot pathway to 6 W/m^2 (~850 ppm CO_2 e) at stabilisation after 2100
RCP8.5	Rising radiative forcing pathway leading to 8.5 W/m^2 (~1370 ppm CO_2 e) by 2100.

Source: van Vuuren et al. (2011)

Figure 2.2: Global temperature change and uncertainty



Note: Global temperature change (mean and one standard deviation as shading) relative to 1986–2005 for the SRES scenarios run by CMIP3 (left) and the RCP scenarios run by CMIP5 (right). The number of models is given in brackets. The box plots (mean, one standard deviation, and minimum to maximum range) are given for 2080–2099 for CMIP5 (colours) and for the MAGICC model calibrated to 19 CMIP3 models (black), both running the RCP scenarios.
Source: Knutti and Sedláček (2012)

for global surface temperature projection until the end of the century, with the RCPs showing a wider range of uncertainty when compared to the SRES.

Regarding climate projections with GCMs, two types of uncertainties should be highlighted: i) *intra*-model uncertainty and; ii) *inter*-model uncertainty. Intra-model uncertainty depends on the emission or concentration assumptions considered and are related to the input data for climate models to perform experiments. In comparison, inter-model uncertainty derives from the distinct results obtained once the climate models (GCMs) from an ensemble are run under different SRES emission or RCP concentration assumptions. In general, recent studies that use climate projections to assess the impact of climate change on water resources use one or more GCMs run under one or more SRES or RCP scenarios. A clear advantage of the SRES and RCP scenarios is that it allows the scientific community to have a basis for comparison among impact studies. However, while scenarios have been used in a wide range of policy-experiments, van Vuuren et al. (2011) state that they should not be interpreted as forecasts or absolute bounds or be seen as policy prescriptive (i.e. no likelihood or preference is attached to any of the individual scenarios of the set). At the same time, the use of the SRES or RCPs in climate research may provide important information for decision-making. A broader discussion on climate change uncertainty and its treatment will be carried out in Section 2.3.1 on page 66.

2.2.1.2 *Downscaling*

The broad generalisations of projected climate change provided by GCMs may be useful for comparing responses at a global scale, however they cannot provide information at scales finer than their computational grid (typically of the order of 200 km), and processes at these unresolved scales are important. In this context, additional technics were developed that seek to address the disparity between the coarse spatial scales of GCMs and observations from local meteorological stations – what is known as *downscaling* (Teutschbein and Seibert, 2012). GCMs do not accurately predict local climate, but the internal consistency of these physically-based climate models provides most-likely estimates of ratios and differences (scaling factors) from historical to predicted scenarios for climatic variables, such as precipitation and temperature (Fowler et al., 2007). Downscaling techniques can be classified in two categories (Chen et al., 2013): *statistical* and *dynamic*.

STATISTICAL DOWNSCALING TECHNICS combine existing and past empirical knowledge to address the disparity between coarse spatial scales of GCMs and point local meteorological observations (Green et al., 2011). This technic uses a statistically-based model to determine deterministic or stochastic relationships (functions) between observed regional climate variables (dependent or predicted variables) which are conditional to large-scale GCM variables (independent or predictor variables). The derived functions between predicted and predictor variables are applied on similar predictor variables from GCM simulation results to estimate the corresponding local or regional climate characteristics. Therefore, this method implicitly assumes that such empirical relations will remain valid in future climatic conditions (Kundzewicz et al., 2007).

DYNAMIC DOWNSCALING TECHNICS explicitly solve the regional physical variables by nesting a higher resolution (20 – 50 km) Regional Climate Model (RCM) within a coarser resolution GCM. Thus, in addition to GCM results, surface layer characteristics are incorporated into the analysis, i.e. topography, vegetal cover, etc. Although this method does not implicitly assume the perpetuity of historic climatic relations, it is data and computational intensive, which limits its use for the large amount of results provided by numerous GCMs (Maurer, 2007). In addition, dynamic downscaling can generate significant errors as it may accumulate GCMs bias to the ones of RCMs (Wood et al., 2004). Taylor et al. (2012), in a review on the GCMs of the CMIP5 ensemble, conclude that the downscaled data cannot be more reliable than the climate model simulation that underlies it – *more detail does not automatically imply better information*. RCMs are attractive to those seeking process understanding and causative simulation, but most downscaling is currently statistical (Green et al., 2011).

A conventional and broadly used statistical downscaling method is the so-called *delta factor approach*, which is a method that makes the output of GCMs useful for catchment scale analysis of hydrological modelling.[8] The method starts with the preparation of coincident predicted and predictor data time series. The predictor data set is obtained from GCM results in the grid corresponding to the local study area, while the predicted data set is a long time series of observed daily or monthly weather information from local meteorological stations that represent an area (e.g. temperature, rainfall, solar irradiance, etc.). The *delta factor* is the ratio between a mean in the future and the historical run. This change factor is then applied to the observed historic time series to transform this series set into a time series that is representative of a possible future climate (Ruiter, 2012).

Although the delta factor approach is considered to be limited, mainly because it does not incorporate the possible (and mostly uncertain) changes between local and large scale climatic variables, this method has been extensively applied in several hydrological studies (e.g. Thompson et al., 2014; Ho et al., 2015; Parkinson and Djilali, 2015; Teotonio et al., 2017). The advantage of the delta factor approach is its simplicity and its ability to minimise GCM errors, assuming that the modelling bias for the future is equivalent to that of the present. This can be particularly important for precipitation projections, in which differences between observed and GCM computed values can be relevant (Cisneros et al., 2014). Roy et al. (2010) present the pros and cons of using the delta method approach technic, pointing out that it is of proper use when the number of basins in matter are several and when local climate measurement time series for the use of enhanced downscaling procedures is absent (e.g. in the case of developing

8 Other statistical downscaling methods include: constant scaling (CS), daily scaling (DS), daily translation (DT), local intensity scaling (LOCI), daily bias correction (DBC) and quantile mapping (QM). See Chen et al. (2013).

countries).[9] Ultimately, the selection of a method to downscale and further model the hydrology of a defined area depends on the purpose of the results, i.e. *understanding the behaviour of a specific hydrological system, or generating a series of representative results to be used in subsequent modelling exercises.*

2.2.1.3 *Modelling the hydrological cycle*

Alterations in the hydrological cycle caused by climate change are simulated with different types of hydrological models. These can be classified in: i) physical models, ii) conceptual models, and iii) statistical or empirical models.

PHYSICAL MODELS have their parameters based on measurements, which provides a greater degree of realism at the expense of a large demand for data. This makes it extremely difficult to apply to large hydrographic basins or in regions with problems of access and information collection. Similarly, input data from climate models need high spatial and temporal resolutions that are compatible with those used in hydrological physical models, which depends on the use of downscaling techniques that are capable of reaching such levels of resolution (Cornelissen et al., 2013; Tegegne et al., 2017). The high demand for data from physical models severely limits its application on climate change impact studies.

CONCEPTUAL MODELS are based on conceptual relationships of the hydrological cycle, with their parameters being calibrated rather than measured. It is tried, through different techniques, to identify a combination of parameters that generates a behaviour of the model consistent with observed data or with historical experience (Devkota and Gyawali, 2015; Yan et al., 2015).

STATISTICAL MODELS are purely based on empirical relationships between climatic variables and hydrological behaviour. Statistical models include multiple regression models, where flow is estimated as a function of climatic variables such as rainfall and temperature. By not explicitly explaining the physical relationships behind the mechanism by which climatic variables influence the flow of a river basin, statistical models are often called "black box" models (Serrat-Capdevila et al., 2007; Shamir et al., 2015). However, the simplicity and ease of application of such models make them interesting methodological options, assuming that the model is well adjusted.

9 Critics to the delta method consist on its non-ability to handling the modelled changed in a proper statistics manner. Some of the outliers can be washed out when working with averages. For further discussion and applicability of the delta method refer to the findings of Roy et al. (2010)

According to Xu (1999), all types of hydrological models have advantages in different applications. More complex models in terms of structure and data input may yield suitable results for a wide range of applications, but high computational effort and high data demand may limit its use. Although less comprehensive, simpler models can provide results that are appropriate to a specific goal with reduced computational and data demand. Therefore, the choice between models is strongly related to the purposes for which hydrological modelling serves, or to the choice between *the simple models that can be used and the complex models that need to be used.*

Once the source of information on climate impacts (e.g. GCMs), the concentration scenarios (e.g. RCPs, SRES), the downscaling method (e.g. statistic, dynamic) and the hydrological model (e.g. empirical, conceptual or physical) have been defined, some caveats of the five-step assessment method that was shown in Figure 2.1 on page 36 are discussed in the following paragraphs.

According to Arnell (1992), one of the main hypotheses of this methodological approach is that the hydrological model remains valid under different climatic conditions, that is, that the parameters of the model do not only reflect the relations between climate and current flow. For example, vegetation cover plays a key role in the hydrological cycle, especially at the local level. Possible future changes in biomass production caused by climate change – in addition to anthropogenic activities, such as deforestation and other changes in land use – is an element of great uncertainty in the analysis of impacts of climate change (Hua et al., 2015). The increase in CO_2 concentration can also boost the growth of some plants, which can increase evapotranspiration in certain areas (Cisneros et al., 2014). Only few studies include a dynamic vegetation cover model into the hydrologic model (Dodds, 2010), and the few that do, consider only large scales (GCM) and not basin level.

Another drawback, pointed out by Loaiciga et al. (1996), is that given the natural uncertainty of hydrological regimes in the current climate (evident in the first step of the method), it is difficult to distinguish climate change-induced variations from those inherent in the hydrological cycle – *signal-to-noise* interpretation problem. In this sense, several studies use more than one hydrological model or more than one downscaling method, explicitly in the attempt to isolate the bias of each stage – particularly for steps one and two, mentioned in Figure 2.1 on page 36. Uncertainty in climate change and water resources modelling will be further discussed in Section 2.3.1 on page 66.

Although the impacts of climate change on the hydrological cycle have been the focus of several studies, few studies assess the impacts on groundwater and the relationship between rivers and hydraulically connected aquifers (Cisneros et al., 2014). The IPCC

(2007) stated that a lack of necessary data has made it impossible to determine the magnitude and direction of groundwater change due solely to climate change. Green et al. (2011) provide an overview and synthesis of the key aspects of subsurface hydrology (soil water, deeper vadose zone water,[10] and unconfined and confined aquifer waters), related to climate change. The relation between climate variables and groundwater is considered more complicated than with surface water (Bates et al., 2008), given that groundwater-residence times can range from days to tens of thousands of years, which is likely to delay and disperse the effects of climate change, and challenge efforts to immediately detect responses in the groundwater (Chen et al., 2004).

An additional complication is that the great majority of studies about climate change and hydrology use average impacts, not considering extreme events, such as droughts and floods. Increasingly frequent and intense hydro-climatic extremes in recent decades are accelerating impacts on natural and human systems (IPCC, 2012). El Niño Southern Oscillation (ENSO), which is an example of a cyclical climate extreme, is a major driver of global inter-annual climate variability (McPhaden et al., 2006). Its characteristic warming (El Niño) and cooling (La Niña) phases manifest in flood and drought conditions across many regions of the world (Chiew and McMahon, 2002; Yu and Zou, 2013; Ward et al., 2014; Liang et al., 2016). Jentsch et al. (2007) state that research on extreme events ("event-focused" in contrast to "trend-focused") can only be defined in relation to the system being studied, and the extremeness only by statistics linked to the occurrences of the process itself. Thus, there is the need to take into account information on historical or projected extremes of simulated events (i.e. relative magnitude compared to mean conditions).

Finally, hydrologists have developed interest in simulating flow at various scales for various reasons, such as availability for irrigation, flood control, sediment transport, hydroelectric generation, etc. Thus, the impacts of climate change on water availability cannot be dissociated from the purpose for which this resource is intended. In the case of human needs, socioeconomic development plays a fundamental role in assessing the future availability of water. Changes in the hydrological cycle are not only subject to the impacts of climate change on water resources, since several factors can influence the future use of water as can be seen in Table 2.5 on the next page.

The global view of studies, such as the IPCC AR5 chapter on Freshwater Resources is especially relevant in the motivation for formulating comprehensive mitigation policies

10 The vadose zone, also termed the unsaturated zone, is the part of Earth between the land surface and the top of the phreatic zone, the position at which the groundwater (the water in the soil's pores) is at atmospheric pressure. Hence, the vadose zone extends from the top of the ground surface to the water table.

Table 2.5: Socio-economic impacts on availability of water resources

Factor	Impact
Energy generation	Hydropower energy requires to use free flowing or impounded water resources.
Population growth	The greater the population the greater the demand for water.
Population concentration	The use of water in urban areas tends to be greater than in the rural environment due to waste, leaks and due to the need for sanitation. In addition, the concentration in urban areas can generate pressure on the water resources of specific localities.
Industrial development	Industry is a major consumer of water, although different industrial specialisations may have different impacts.
Increased irrigation	An increasing population will require greater production of food. More efficient irrigation techniques can reduce this effect.
Efficiency in water use	Improved management of water resources can reduce the demand for water.
Environmental restrictions	They can limit access to water resources.

Source: Arnell et al. (2011)

(Cisneros et al., 2014). Such a study includes impacts on: agriculture and food security, land use and forests, human health, supply of water and municipal sanitation, settlements and infrastructure, and economic sectors such as tourism, industry and transport. However, by addressing the problem on a global scale, specific local impacts are not addressed. This makes it difficult to apply the results for the design of local adaptation policies for the various impacts that may arise from changes in the hydrological cycle. In this sense, studies that work on impacts in specific sectors on a scale relevant to policy decisions are of the utmost importance. This is what part of this thesis is about – focusing on the national level impacts of climate change on electricity generation from hydraulic sources.

2.2.2 *Impacts on hydropower electricity generation*

The complexity of hydropower modelling can vary according to the size, type of technology, geographical extension, hydraulic interconnections (cascading in the same river), electrical interconnections (transmission), share in overall generation, etc. Without considering, for now, the characteristics of the plants themselves, basically two factors can influence the complexity of modelling a hydroelectric system:

1. **The overall contribution of hydropower in the generation matrix.** Whether the hydroelectric system is *complementary to* or *complemented by* other sources of electri-

city generation. In systems where the participation of hydroelectricity is small and therefore its role is to complement other sources, the ability to satisfy demand does not depend to a great extent on the hydrological scenario. Thus, the variation in the amount of average energy produced per year by the hydroelectric system is a sufficient measure of the possible impacts of climate change, as for example is the case of the studies of McPhee et al. (2012) for Chile and Hamlet et al. (2010) for the US, both countries with large shares of thermoelectric generation. In comparison, in a system where hydroelectricity is predominant, the variation in the average yearly amount of energy generated is not a good enough measure to evaluate the impacts of climate change. In systems such as this, the reliability of electricity supply depends fundamentally on the monthly hydrological scenario and climatic impacts must use more conservative indicators for analysis, such as *firm capacity*.[11] This is the case, for example, in the studies of Lucena (2010) for Brazil and Seljom et al. (2011) for Norway, both countries with important shares of hydropower generation.

2. **The geographic distribution and level of integration.** Integration can be either in terms of hydraulic connections – such as more than one power plant along the same river or its tributaries – or energetic – through the transmission of electricity in the same interconnected system. The operation of cascading systems should maximise the amount of energy produced not only in an isolated plant but throughout the entire flow. In systems covering a wide territorial extent, in different river basins, integration through electric transmission can help to optimise the operation in scenarios of regionally distinct climatic variations – eventual or seasonal. In such systems, just as plants on the same river cannot be optimised individually, the modelling of the expansion and operation of the system should consider water availability in different basins.

The above detailed factors influence, therefore, the rationality of the operation of the hydropower system, as well as the institutional/legal framework that governs its operation. In small and complementary hydropower systems, the individual rationality of the plant may be prevailing, as well as in free market environments. In larger and more complex systems, the logic of centralised operation makes more sense to optimise the efficiency of the system as a whole. This rationality of the operation must also be present

11 Firm capacity can be defined for a hydroelectric system as the greatest amount of energy that can be obtained considering the worst hydrological scenario, usually based on historical experience. It can alternatively be defined as the largest amount of energy produced in the worst critical period, which in turn consists of the period in which the system's storage capacity goes from the maximum to the minimum without intermediate re-fillings. In other words, it is the period in which the energy accumulated in the reservoirs depletes without a complete replenishment.

in the energy modelling of the possible impacts of climate change. Two examples of contrasting operating rationalities are presented in the studies by Gaudard et al. (2013) focusing on climate change impacts on the management of a single hydropower station and the study of Kannan and Turton (2011) modelling the impact of different hydroclimatic scenarios for the national power system, both of these studies are developed in Switzerland but for different scales of analysis – local and national, respectively.

2.2.2.1 *Energy modelling paradigms*

Computerised tools have been employed to aid investment decision-making in the energy sector. These have become more sophisticated and powerful overtime leading to different approaches and increasing capabilities for disaggregation, uncertainty and even for including climate change impacts. As Connolly et al. (2010) state in their review of computer tools for assessing the integration of renewable energy, *"energy models are employed to assist policy-makers and decision makers by facilitating the exploration of different options of development that leads to gaining high level insights regarding electricity market design, network investment, and in establishing desired energy policies outcomes that are aligned with national/regional or even international objectives."* Extensive reviews of available energy models and their capabilities for informing policy can be found in the studies of Jebaraj and Iniyan (2006), Connolly et al. (2010), Bhattacharyya and Timilsina (2010), Pfenninger et al. (2014), Chiodi et al. (2015) and OLADE (2017b).

There are two main energy modelling paradigms: *top-down* and *bottom-up*. Top-down approaches break down a system to gain insight into its compositional sub-systems, while a bottom-up approach puts together elements of a system to give rise to grander systems (Kesicki, 2012).

TOP-DOWN MODELS take an aggregated view of the energy sectors and the economy when simulating economic development, related energy demand and energy supply (Herbst et al., 2012b,a). The top-down label comes from the way modellers apply macroeconomic theory and econometric techniques to historical data on consumption, prices, incomes, and factor costs to model the final demand for goods and services, and the supply from main economic sectors (i.e. energy, transportation, residential, agriculture, and industry) (Nakata, 2004). Examples of top-down energy models are macro-economic models which use hybrid input-output matrixes with the inclusion of energy flows to describe transactions among economic sectors (Guilhoto, J. J. M., Sesso Filho, 2005; Mayer, 2007; Rathmann et al., 2012; Miller and Blair, 2009) and computable general equilibrium (CGE) models that construct the behaviour and interrelations of economic agents based on microeconomic principles (van Beeck, 2003). According to Hourcade et al. (2006), what top-down energy models seem to lack, in general, is technological flexibility beyond current practice. If the input substitution elasticities, critical to technological response in top-down models, are estimated from historical data, there is no guarantee that the values for these parameters would remain valid in a future with ambitious policies for environmental improvement, i.e. shaped by induced technical change (Solaymani and Kari, 2014; Martinsen, 2011; Cai and Arora, 2015). Currently, macroeconomic energy models are often being used to evaluate the economic costs and environmental effects in the whole economic system of energy or climate policy instruments, such as CO_2 taxes, emission trading systems (ETS), feed-in tariffs of renewable energies, etc.

BOTTOM-UP MODELS are built on "engineering thinking". Their relatively high degree of technological detail enables modelling of components of the system. Thus, it is generally a well-suited approach when the purpose of the model is to analyse specific changes in technology or command-and-control policies. For instance, when modelling the expansion plans of electricity generation capacity, a bottom-up approach is more appropriate because of its ability to capture many energy-related aspects of the system in a disaggregated form (Bhattacharyya and Timilsina, 2010). This approach, for instance, makes it possible to analyse how investing in renewable energy would impact the total energy system cost. According to Herbst et al. (2012b), bottom-up models use a business economics or social planner approach for the economic evaluation of the technologies simulated. They usually cannot consider macroeconomic impacts of energy or climate policies or related investments. Regarding the mathematical form, bottom-up energy models have been developed in the form of simulation or optimisation models, and more recently of multi agent models (or agent-based models) (Mundaca et al., 2010; OLADE, 2017b).

To overcome the above-mentioned weaknesses and limitations of conventional top-down and bottom-up energy models, energy modelling is currently moving in the direction of hybrid energy system modelling. This approach combines at least one top-down macroeconomic model with at least one set of bottom-up models for each final energy sector and the conversion sector (Herbst et al., 2012a). According to Hourcade et al. (2006) a high-quality hybrid model system should incorporate at least three properties: i) technological explicitness, ii) microeconomic realism and iii) macroeconomic completeness. The simplest form of linking top-down and bottom-up approaches, also called 'soft linking', is the manual transfer of data, parameters and coefficients. If this transfer is further evolved using automatic routines, a 'hard link' is established between the different models. Soft-linking approaches have been carried out, for example, by Fortes et al. (2014b) in their study for Portugal where a soft-link between the bottom-up TIMES[12] energy system optimisation model and the CGE GEM-E3[13] model is done, or in the study by Soria et al. (2016) in the study of Concentrated Solar Power (CSP) in Brazil where a soft-link between a dispatch model (REMIX) and and energy system optimisation model (MESSAGE) is done. Hard-linking examples include the work by Manne (1992) and the MESSAGE-MACRO[14] model (Messner and Schrattenholzer, 2000) and more recently the stand alone TIMES-Macro hard-linked top down/bottom up linkage (Kypreos and Lehtila, 2014).

The use of either of these approaches (top-down or bottom-up) is determined by the modelling goal and scope (Decarolis et al., 2017). However, because this research hopes to understand how different aspects and components of the energy system model are impacted by climate change, a bottom-up approach will be used.

2.2.2.2 *Modelling climate change impacts on hydropower systems*

Bottom-up models used to study the impacts of climate change on hydropower systems can be categorised in two groups: *simulation* and *optimisation* models:

SIMULATION MODELS are used in energy modelling as descriptive tools. These models attempt to provide a descriptive, quantitative illustration of energy demand, supply and/or conversion based on exogenously determined drivers and technical data (e.g. income, population, government policies, energy prices, etc.) (Herbst et al., 2012b). These models help the decision maker (or modeller) to get a deeper understanding of how the system would behave under different scenarios such as varying policy instruments or relationship between two variables in a system. Put in another way, these models are used to answer 'what if' type of questions. The model outcome is heavily influenced by the input assumptions and data. Thus, it is difficult to explicitly model least-cost investment decisions of other optimal behaviour under constraints. Econometric models are a type of simulation models which in the context of the impacts of climate change impact on hydropower make use of the historical empirical relationships between flow and electricity generation to project the effects of variations in flow regime. This method, although

12 The Integrated MARKAL EFOM System
13 General Equilibrium Model for Economy-Energy-Environment
14 Model for Energy Supply Strategy Alternatives and their General Environmental Impact with a Macroeconomic extension

severely limited because it does not include considerations regarding the factors and parameters influencing hydroelectric power production, can be applied when the availability of technical data regarding the hydropower stations and the electricity system are scarce.

OPTIMISATION MODELS intend to define the optimal set of technology choices to achieve a specific target at minimised costs under certain constraints (Bazmi and Zahedi, 2011). They try to generate possible futures that lower the cost of the system. According to Baños et al. (2011), the operating principal of an optimisation model is to minimise the output of what is called the "objective function", which in concept seeks to support an optimum allocation of resources, technologies and relevant services under several constraints. The outcome represents the best solution (e.g. least-cost) for given variables while meeting the given constraints e.g. least emissions (Nakata et al., 2011). Outcomes from optimisation models can be even more sensitive than simulation models to input assumptions, e.g. penny switching behaviour — the model endogenously selecting a technology or energy commodity that is only slightly cheaper that the possible alternative. A flip-flop effect (or all or nothing effect) can appear in the least-cost portfolios when performing sensitivity analysis with only small variations of the input parameters, particularly prices. A complete review of optimisation modelling of energy systems can be found in Zeng et al. (2011).

The use of simulation models to assess the impact of climate change on hydropower has focused in representing the behaviour of energy producers applying some operating rule. For example, Harrison and Whittington (2002) used a simulation model of the operation of the reservoir of the Batoka Gorge Dam project of the Zambezi river that considers water spillage[15] and evaporation of the reservoir to project monthly power generation. The model used by Hamlet et al. (2010) simulates the operation of a system of hydropower stations in the Pacific Northwest of the US including the impacts of irrigation in the energy model to take into account for additional stresses on the dam.

The model used by De Lucena et al. (2009) simulates the operation and dispatch of individual power plants while considering the synchronised operation of the hydro-thermal power system in Brazil. Dale et al. (2015) model the impacts of climate change on the Sacramento area by linking the hydrological model WEAP[16] and the simula-

15 Water spillage correspond to vents from the reservoir that do not pass through the turbines. This is the case when there is excess water in the reservoir or level of downstream flow must be at a minimum as defined by law. The aim of this ‘ecological flow restriction’ is to maintain ecological processes (such as fish migration) and allow continued nutrient and sediment transport downstream.

16 Water evaluation and planning.

tion (account-based) energy model LEAP[17]. Both tools feature mass balance accounting frameworks, simple dispatch rules for regulation of resource supply and climate sensitive functions. Dale et al. do not base their hydroclimatic scenarios on GCM projections, but rather on four extreme hypothetical scenarios to represent the impact of future temperature and precipitation extremes. They argue that GCM-based scenarios are too uncertain and do not bring any additional gain to the analysis.

There are also studies that use simulation tools to assess the impact of climate change on hydropower at a global scale. For example, van Vliet et al. (2016a) developed a soft-linked hydrological-electricity simulation modelling framework to assess the vulnerability of the world's current hydropower and thermoelectric power generation system to changing climate and water resources. The final conclusion of this study is that transitions in the electricity sector with a stronger focus on adaptation, in addition to mitigation, are thus highly recommended to sustain water-energy security in the coming decades. On a regional scale, the study from OLADE-BID-AEA (2013), assesses the vulnerability of hydropower in Central America. The study models seven hydropower stations in Central America that capture the different uses of hydropower in the region – stations with and without dam, Atlantic and Pacific basins, and different precipitation patterns, etc. They also seek to calculate the firm capacity factor of each hydropower station. The main characteristic of simulation models used to assess the impact of climate change on hydropower systems is that economic feedbacks of the assessed water constraints and related adaptation options (for example, on energy prices, supply-demands technology options) for the overall energy system are not usually modelled, which is what optimisation models seek to address.

Regarding studies that have used econometric models to assess climate change impacts on hydropower are the study of Iimi (2007), who estimated the impacts of climate change on hydropower for three projects in India, Sri Lanka and Vietnam. The study applies a simple vector autoregressive model to forecast future hydrological series and evaluate the resulting impact on hydropower projects. The author concludes that having larger installed capacity and some storage capacity might be useful to accommodate future hydrological variations and seasonality. Similarly, the study of CEPAL (2012), that assesses the vulnerability to climate change of the Chilean hydropower sector, develops an exponential regression model using the historic relations between runoff, temperature and generation.

The study of Grijsen (2014), assesses the impact of climate change on hydropower in Cameroon, by developing a series of empirical econometric regression analyses for

17 Long-Range Energy Alternative Planning System.

a specific basin based on observed precipitation, temperature and streamflow data at multiple monitoring stations. The authors goal is to derive a series of 'climate elasticities' which show the sensitivity of runoff and hydropower generation to hydro-climatic variables – temperature, precipitation and evapotranspiration. The authors highlight the practicality of this econometric approach to avoid time consuming and data intensive hydrological and energy modelling, in addition to the large number and uncertainties of GCMs.

Other approaches can also be undertaken to assess effects on large regions for which little information is available. In the projections of existing hydropower potential in Europe,[18] Lehner et al. (2005), for example, simply applied physical relationships to flow and altitude data. In addition, the authors had to make simplifications for lack of specific information: i) generation is proportional to the installed capacity to the same extent in all the plants, implying in unique values for efficiency and capacity factor,[19] and ii) the effect of flow variations affects the energy produced directly in the same proportion, which excludes the role of reservoir management. The study of Lehner et al. did not incorporate the possible impact on future developments and additional potential.[20]

Similarly, an assessment of the global technical and economic hydropower potential at the global scale is presented by Gernaat et al. (2017). This study used high-resolution hydrographic discharge (15″× 15″; 450 m at the Equator) and elevation (3″× 3″; 90 m at the Equator) maps to calculate cost-optimal dimensions and associated production potential of two types of hydropower systems: river power plants and diversion canal power plants (following the definitions of Wagner and Mathur, 2011). The authors considered that globally, hydropower projects would: i) follow cost equations from Norwegian and US hydropower tender and contracts (which might underestimate the costs in developing countries), and ii) deploy fully in all rivers across the globe, excluding only the first 200 km upstream of basin outlets of rivers deeper than 4 m (river mouth restriction) and the area in the vicinity of large bodies of water such as lakes or wide rivers. These assumptions overlook policy and other social factors that might impact the development of hydroelectricity. Gernaat et al. also assessed the effect of climate change. Globally, a slight increase is seen (2 – 10%) that consistently occurs in Africa (4 – 18%) and Asia Pacific (3 – 6%), while Europe shows a consistent decrease (-2 – -3%). North and South America are less consistent over across the climate models.

18 Existing potential is defined as the average annual capacity of hydroelectric generation by country.

19 Capacity factor is defined as the ratio between what a power plant (or system) generates of energy and what it would generate if it worked at full power all the time.

20 The impact on future uses can be incorporated in the analysis provided there are reliable estimates for the technical parameters of the plants and the behaviour of the natural flow affluent to the projected reservoirs.

When using optimisation models to assess the impact of climate change on hydropower, most studies focus on the operation of a hydropower system where the objective function minimises variable cost, subject to operational constraints – usually synthetic time series of inflow based on historic data. The objective function can also consist on the maximisation of revenue from the sale of electricity, based on price scenarios, such as the studies of Vicuna et al. (2008) for California's hydropower plants and Gaudard (2015) for a pump-storage facility in Switzerland. If the broader power sector is considered, the optimising of the operation of hydropower and thermoelectric units is the objective, i.e. assess the shift that the non-hydro capacity mix must undertake to ensure system robustness, thus providing least-cost adaptive capacity to the system. For example, the study of Parkinson and Djilali (2015) elaborated an electricity-planning framework for British Columbia incorporating least-cost adaptation to hydro-climatic change. According to the study, this imposed flexibility requirements from thermal generation is estimated to increase the total cost of long-term electricity system operation between 1 – 7%. This maximisation approach is best used for market driven energy sectors.

In hydrothermal power systems, as the ones in South America, a possible objective function is to minimise the expected long-term generation cost over the planning period. Only a few studies have been found that go beyond impact assessment and, with the aid of an energy system optimisation model, pursue quantification of climate change impact and adaptation costs. Among the few, Lucena (2010) assesses the impact of climate change on the Brazilian energy system, while focusing mostly on the hydropower system. The study uses the MESSAGE[21] energy system optimisation model from the International Institute for Applied System Analysis (IIASA) applied to the Brazilian energy system (MESSAGE-Brazil), to calculate least-cost adaptation alternatives for the projected impacts. Seljom et al. (2011) assess the impact of climate change on the Norwegian energy system using by modelling the energy sector with the energy system optimisation model MARKAL.[22] This study indicates that in Norway, climate change will reduce the heating demand, increase the cooling demand, have a limited impact on the wind power potential, and increase hydropower potential.

More recently Teotonio et al. (2017) assess the impacts of climate change on hydropower generation and the power sector in Portugal by 2050 with a TIMES[23] energy system optimisation model. Results show that hydropower generation may decrease by 41% in 2050. However, hydropower will remain one of the most cost-effective technologies in the Portuguese power sector, although it has almost been fully exploited.

21 Model for Energy Supply Strategy Alternatives and their General Environmental Impact.
22 Market allocation
23 The Integrated MARKAL and EFOM System

The study of van der Zwaan et al. (2018), which assess the prospects of hydropower development in Ethiopia, also uses the TIMES methodology but with the global model TIAM-ECN[24] energy system optimisation model and disaggregates Ethiopia from the African region to assess low-emission development strategies in the context of the ambitious hydropower development plans of the country. The study shows that by 2050, Ethiopia's electricity supply will need to grow 50-fold and rely largely on hydropower to supply its growing demand while maintaining low emission levels. The study of (Lucena et al., 2018) goes beyond using a single model and performs a multi-model comparison to assess the impact of climate change on hydropower in Brazil and on the overall energy system. In this study, *ceteris-paribus* is also used to perform the analysis of climate change impacts only on hydorpower, while neglecting all other climate impacts on the power sector. And although, this study uses an ensemble of 16 GCMs for scenarios RCP4.5 and RCP8.5, only two representative GCM scenarios are used to rerpresent low and high impacts. The latest study found is that of Sridharan et al. (2019), who do an assessment on resilience of the Eastern African electricity sector to climate driven changes in hydropower generation. This study uses a soft-link between a conceptual water model (WEAP) with the energy system optimisation model OSEMOSYS, to model the systems of 10 countries in East Africa, although only use a limited numbero of 6 GCMs.

The mentioned studies have modelled the whole energy system with optimisation models but focused particularly on the impact that climate change has on hydropower and therefore on the rest of the system. However, they have some shortcomings that are worth mentioning and that will frame the literature gaps that this thesis seeks to tackle:

1. Hydropower's operational characteristics are not modelled in detail. Most optimisation models do not distinguish hydropower according to the operation characteristics of run-of-river and reservoir-based facilities beyond assigning an average capacity factor for the technology (e.g. Teotonio et al., 2017). In addition, hydropower's availability is usually only detailed at the aggregated intra-annual (seasonal) level (e.g. Seljom et al., 2011; Kannan and Turton, 2011), that can wash out critical months with low runoff.

2. The typical 'discrete' investment characteristics of large hydropower projects is not considered (e.g. van der Zwaan et al., 2018). Most energy system optimisation models are strictly linear models that can build continuous amounts of technology-specific capacity in any model time period. While this is a reasonable approxim-

24 TIMES Integrated Assessment Model from the Energy Research Centre of the Netherlands (ECN)

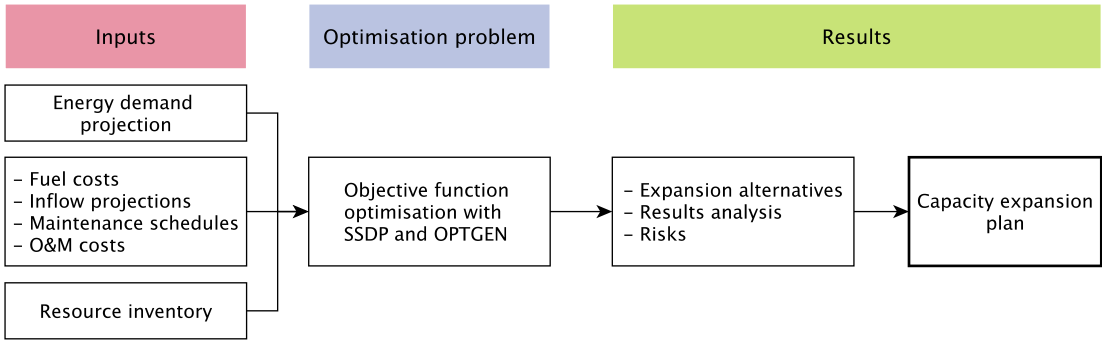
ation for many technologies, in some cases (e.g. hydropower and nuclear power) it is appropriate to account for the granularity of investments by constraining the model to use discrete sizes of particular technologies, a method known colloquially as "lumpy investment."

3. Most studies use a small number of emission scenarios of GCMs to characterise climate change uncertainty that usually show the same trend and direction of change. Using a larger number of GCMs could lead to evidencing more varied, and many times contradicting, projections of climate change.

4. Finally, the time horizon of the analysis and the consideration of other uncertainties apart from climate change might be of relevance. Given that climate change impact assessments on hydropower are carried out for the long-term, uncertainties regarding prices may add to those inherent in these type of studies; particularly when using energy system optimisation models that use energy resources prices and technology cost information to find a least-cost system configuration. This thesis will focus on the uncertainties of fossil fuel prices and power generation technologies cost because these parameters are the most relevant in the decision process to favour or restrict hydropower deployment, particularly when hydropower competes with traditional fossil fuel generation options. One the one hand thermal generation has low infrastructure costs, less prone to cost overruns but vulnerable to fossil fuel price volatility, on the other hand hydropower has high infrastructure cost, is prone to cost overruns, but vulnerable to climate change. This decision trade-off is the one this thesis specifically seeks to address, although in an integrated analysis many other uncertainties could be considered to answer other sets of research questions (demography, energy demand, GDP, etc.)

Table 2.6 on page 59 shows reviewed studies found in the literature regarding the impacts of climate change on hydropower systems. The intention of the table is to show the combination of hydrology and energy modelling tools that studies have used, by detailing emission scenarios, number of GCMs, downscaling method, hydrological model and hydropower/energy model (according to the standard method shown in Figure 2.1 on page 36). Among the countries that have many studies is the US (mainly the Pacific Northwest), Norway, Canada and Brazil. Studies that use energy system optimisation models focus on the interaction of hydropower variability with other parts of the energy sector usually at the national scale (Teotonio et al., 2017; Seljom et al., 2011; Lind et al., 2013; De Lucena et al., 2009; van der Zwaan et al., 2018); while studies that use simulation models tend to focus on the hydropower project level or on a single river

Figure 2.3: Generation capacity expansion planning process in Ecuador



basin in which reservoir operation is modelled (Markoff and Cullen, 2008; Harrison and Whittington, 2002; Parkinson and Djilali, 2015). Econometric studies are used for data scarce regions or large geographic regions in which the particularities of the operation of the hydropower system cannot be captured and focus in finding global and regional trends (van Vliet et al., 2016a; Spalding-Fecher et al., 2017). The number of countries for which the impacts of climate change on water resources and hydropower is continuously increasing.

Finally, it is important to highlight once again that the complexity of the system will determine the approach to be used in assessing climate change impacts. In cases of complex systems at a national scale, such as the Ecuadorian one, a single model may not be sufficient to describe the operation of the hydropower plants and its interaction with the rest of the energy system. The current expansion and operation planning of the Ecuadorian power system, carried out by the Ministry of Electricity and Renewable Energy (MEER),[25] is based on a combination of models that approach the issue with different degrees of detail and planning horizons (MEER, 2017a).

To elaborate the Electricity Master Plan 2016-2025 (MEER, 2017a), two computational tools have been used: OPTGEN (Model for generation expansion planning and regional interconnections), and SDDP (Stochastic hydrothermal dispatch with network restrictions), both commercial software provided by PSR (PSR, 2018). Figure 2.3 depicts this capacity expansion planning process that is currently undertaken in Ecuador. The OPTGEN model, starts with an exogenous demand forecast and project inventory, and determines the least-cost expansion plan (investment, operation and maintenance). These results are subsequently integrated into the SDDP model, which considers the uncertainty of runoff and the operational restrictions of generation plants. The SDDP model calculates the stochastic operational policy of least-cost dispatch through a probabilistic

25 In May 2018 the Ministry of Electricity and Renewable Energy was dissolved and became part of the Ministry of Energy and non-renewable resources.

analysis. It generates multiple equiprobable hydrological scenarios, based on simulated multiple future economic dispatch scenarios to cover the projected electricity demand. From the probabilistic results, the economic dispatch with expected values are obtained, and with different probabilities of exceedance. Subsequently, compliance with the energy reserve margins is verified, as well as the energy supply reliability criteria for power reserve: VERE (expected value of power rationing) and VEREC (expected value of power rationing conditional). Estimated fuel consumption and CO_2 emissions are also determined.

However, a major drawback of this planning process is that its time horizon is maximum of 10 years, limited by the number of years that can be assesses at the hourly level with the mentioned models. Considering that hydropower is long-lived, with economic lifetimes of 30 years and operational lifetimes of over 75 years, and that the impacts of climate change are expected by mid-century, it seems rather myopic to plan the system for only a 10-year horizon. It must be mentioned that this thesis presents the first approach of modelling Ecuador's energy system with an energy optimisation model until year 2050.

Table 2.6: Reviewed studies that assess climate change impacts on hydropower generation

Author	Country/region	Emission scenario	Number of GCMs	Downscaling	Hydrological model	Energy model
Harrison and Whittington, 2002	Zambia	Hypothetical	3	No	Physical (WATBAL)	Simulation (Reservoir and electricity market model)
Lehner et al., 2005	Europe	A1b	1	Delta method	Conceptual (WaterGAP)	Simulation
Iimi, 2007	India, Sri Lanka and Vietnam	A1a	1	Delta method	Statistical	Simulation (Econometric)
Vicuna et al., 2008	US/Sierra Nevada California	A2, B1	2	Delta method	Physical (VIC)	Optimisation (Linear programming model)
Markoff and Cullen, 2008	US/Pacific Northwest	A1B, A1T, A1F1, A2, B1, B2	7	Delta method	Physical (VIC)	Simulation (ColSIM reservoir model)
De Lucena et al., 2009	Brazil	A2, B2	1	Delta method + RCM (PRECIS)	Statistical	Optimisation (MESSAGE)
Hamlet et al., 2010	US/Pacific Northwest	A1b, B1	20	Delta method	Physical (VIC)	Simulation (ColSIM reservoir model)
Madani and Lund, 2010	US/California	Hypothetical	-	Delta method	Statistical (Regression analysis)	Optimisation (EBHOM)
Thorsteinsson and Björnsson, 2011	Nordic countries	A1B	7	11 RCM	Conceptual	Simulation (EMPS)
Vicuña et al., 2011	US/California	A2, B2	6	Delta method	Physical (VIC)	Optimisation (Sequential multistep linear programming)
Escobar et al., 2011	Latin America	A2, B2	Ensemble average	Delta method	Conceptual (WEAP)	Simulation (LEAP)
Seljom et al., 2011	Norway	IS92a, B2, A2, CMIP2, AIB, 1.62xCO2,	5	RCM - HIRHAM	Conceptual (HBV)	Optimisation (MARKAL)
Golombek et al., 2012	Western Europe	A1B	20	Delta method	Physical (VIC)	Simulation (LIBEMOD)
McPhee et al., 2012	Chile	A2, B2	1	Delta method	Conceptual (WEAP)	Simulation (Econometric)

Lind et al., 2013	Norway	-	10	RCM	Conceptual	Optimisation (TIMES)

Table 2.6 (continued): Reviewed studies that assess climate change impacts on hydropower generation

Author	Country/region	Emission scenario	Number of GCMs	Downscaling	Hydrological model	Energy model
OLADE-IADB, 2013	Central America	A2, B1, A1B	4	Delta method	Statistical	Simulation
Grijsen, 2014	Cameroon	A1B	15	Delta method	Statistical (Regression w/elasticities)	Econometric (Regression with elasticities)
Dale et al., 2015	US/Sacramento	Hypothetical	-	-	Conceptual (WEAP)	Simulation (LEAP)
Parkinson and Djilali, 2015	Canada/British Columbia	B1, A1B, A2	8	23 RCM	Physical (VIC)	Optimisation (hydropower and thermoelectricity model)
van Vliet et al., 2016a	Global	RCP2.6, RCP8.5	5	Delta method	Physical (VIC)	Simulation
Shrestha et al., 2016	Nepal	RCP4.5, RCP8.5	3	Statistical	Physical (SWAT)	Simulation
Teotonio et al., 2017	Portugal	A2, B2, RCP4.5, RCP8.5	1	Delta method	Statistical	Optimisation (TIMES)
Spalding-Fecher et al., 2017	South African Power pool	A2, B1, A1B, RCP4.5, RCP8.5	22 (SRES), 11(RCP)	Statistical	Conceptual (WEAP)	Simulation (LEAP)
Gernaat et al., 2017	Global	RCP8.5	2	High-resolution hydrographic maps	Conceptual (LPJmL)	Simulation
van der Zwaan et al. 2018	Ethiopia	RCP2.6	1	Statistical	Conceptual (REBASIM)	Optimisation (TIAM-ECN)
Lucena et al. (2018)	Brazil	RCP4.5, RCP8.5	16	Delta method	Conceptual (GWAM)	Multi-model (ADAGE, COPPE-COFFEE, GCAM, IMAGE, MESSAGE-Brazil, Phoenix_6LA and TIAM-ECN)
Sridharan et al. (2019)	East Africa	A1, A1B, A2, RCP4.5, RCP 8.5	6	Statistical	Conceptual (WEAP)	Optimisation (OSEMOSYS)

2.2.2.3 *Adaptation to climate change impacts in the energy sector*

Impacts of climate change will cause socio-economic costs (and benefits), which are hard to determine. These costs include not only the direct damage caused by the impacts, but also the costs of adapting to the new climatic conditions (Kundzewicz et al., 2007). Identifying adaptation needs requires an assessment of the factors that determine the nature of, and vulnerability to, climate risks (climate change vulnerability and impacts assessments) and an assessment of adaptation options to reduce risks (adaptation assessment) (Noble et al., 2014). Identifying the vulnerabilities of the energy sector to climate change is essential for the design of adaptation policies, since the concern about the impacts of climate change can affect the perception and evaluation of the technological alternatives and the design of national energy policy (DOE, 2015). In the context of climate change, adaptation can be defined as: *strategies that allow practitioners to prepare for the unavoidable effects of climate change, either by minimising negative impacts or exploiting potential opportunities* (Gregg et al., 2018).

According to Noble et al. (2014), adaptation can be described as a function of several factors, such as economic and natural resources, access to technology and information, infrastructure and institutions. Adaptation measures, however, are rarely taken only in response to climate change, and are often part of broader initiatives, such as the UN Sustainable Development Goals (Nerini et al., 2018). Economic development, by itself, is a way of reducing vulnerability to climate change and could therefore be considered as adaptation (Hallegatte et al., 2011). The relationship between economic development and adaptation is therefore rather narrow, since there are several "no-regret" decisions that are made due to other reasons but help to reduce negative impacts of climate change (Callaway, 2004; Castells-Quintana et al., 2018). It may therefore be difficult to distinguish between adaptation measures and measures that are taken independent from climate change.

At the same time, this implies that various adaptation policies can be implemented at low cost, since adaptation has synergies with other policies in different areas. For example, synergies between adaptation and mitigation are interesting because achieving both objectives can increase the cost-benefit ratio of measures and make them more attractive to financing (Vogt-Schilb and Hallegatte, 2011). Although adaptation measures may be autonomous, the adoption of measures which are directly geared to adapting to climate change – such as dams against rising sea levels, reinforcing structures against storms and hurricanes, investing in additional electric generation capacity, etc. – usually involves projecting impacts and comparing their costs with the costs of possible mitigation measures.

However, comprehensive estimates of the costs and benefits of adaptation have so far been scarce and the literature on this subject is still quite limited and fragmented in sectoral and regional terms (Gregg et al., 2018). Adaptation has tended to lag behind mitigation efforts both in research and in the climate negotiations. In part this is because adaptation and development specialists, governments, NGOs, and international agencies have found it difficult to clearly define and identify precisely what constitutes adaptation, how to track its implementation and effectiveness, and how to distinguish it from effective development (Arnell, 2010; de França Doria et al., 2009).

Schaeffer et al. (2012) states that, although the energy sector is vulnerable to climate change, little research has been produced on the subject and modelled adaptation mechanisms[26] is seldom employed. In this sense, climate impacts research is fundamental in developing tools to assist energy planners and policy makers to avoid unexpected surprises and overcome potential energy system bottlenecks. Much of suggested adaptation opportunities for the energy sector appear as appendices to studies that focus on the impacts of climate change. For example, van Vliet et al. (2016a) in a study to assess the global impact of climate change on hydropower and thermoelectric generation, provides a list of possible adaptation options for the electricity sector that range from increases in efficiencies of hydropower plants to increases in efficiency of thermoelectric power plants and replacing hydropower generation by base-load renewables (e.g. geothermal, biomass).

Though van Vliet et al. assess the potential these measures have to reduce water demand; no costs are not presented and it is stated that a comprehensive understanding of future water constraints requires incorporating the physical impacts from the study into economic models of the energy system. Such an integrated approach would allow more realistic adaptation projections, informed by economic, technical and physical constraints.

In an analysis of possible impacts and resilience solutions to climate change for energy infrastructure in the US (DOE, 2015), adaptation measures that can be taken regardless of the occurrence of impacts, such as energy efficiency standards, better location for new energy infrastructure and energy planning and management are discussed. However, the adaptation measures suggested for the energy sector is restricted to almost qualitative discussions. The modelling of adaptation alternatives, their costs and be-

26 Modelled adaptation uses economic models to predict human behaviour against the impacts of climate change (Tol et al., 1998).

nefits is little used in the adaptation literature, which constitutes a good area for the development of studies.

The use of energy system optimisation models, however, is subject to the limitations of this type of approach. Such models assume that actions are guided by the economic rationality of maximising welfare under the market or social planner point of view. This type of analysis can be interpreted according to Tol et al. (1998) in two ways : i) positively, where the model describes what decision-makers do; ii) normatively, directing the way in which the decision makers must act. In the first case, the model must be capable of representing in a faithful way the circumstances of the sector that it is intended to explain, even considering market distortions. Given the difficulty in doing this, the normative use of this type of modelling becomes more pertinent, pointing out directions and trends that are overshadowed by market or government failures. Regardless of its use, however, this form of approach must be reinforced by broader qualitative analyses, where the role of stakeholders is fundamental (Li, 2017).

Only a few studies have been found that go beyond qualitative climate change impact assessment and, with the aid of energy system optimisation models, pursue quantification of impact and adaptation costs (see Table 2.6 on page 59). Ciscar and Dowling (2014) reviewed the integrated assessment of climate impacts and adaptation in the energy sector. They affirm that – *"There is a vast amount of work that needs to be done in order to better understand the vulnerability of the energy sector, which is economically wide-reaching, but possibly has relatively low-cost adaptation options compared to other sectors when taking account the timescales of impacts and life-times of energy infrastructure."* Energy system optimisation models can help assist in this challenge, not only in the technical aspect of defining reliable system configurations, but also in quantifying the monetary flows to achieve them.

2.2.3 *Climate projections for Ecuador*

Regarding future trends on precipitation, temperature extremes and on dryness and drought, Chapter 3 of the IPCC AR5 (IPCC, 2014c) identifies the two regions which present an interest for Ecuador and therefore for this literature review: The Amazon and the West Coast of South America. For the Amazon region, the projections estimate: hot days likely to increase and increase in heavy precipitation events. For the West Coast of South America: hot days likely to increase and increase precipitation in tropics. However, the Freshwater Resources chapter of the IPCC AR5 (Cisneros et al., 2014) presents contradictory findings for South America as a whole. Projections from the CMIP3 regional and high-resolution global models run for the SRES A2 emission scenario show that by the end of the 21st century, there is a consistent pattern of increase of precipitation in south east South America, northwest Peru, Ecuador, and western Amazonia. At the same time, decreases are projected for northern South America, eastern Amazonia, central and north eastern Brazil, the Altiplano in Bolivia, and southern Chile. Given this uncertainty of events for precipitation, the Freshwater Resources chapter, states that: *"Regarding runoff and stream flow projections, there is very considerable uncertainty in the magnitude and direction of change, specifically in large parts of South America."*

The IPCC AR5 has also developed a regional outlook for impacts, adaptation and vulnerability in Central and South America (Magrin et al., 2014). Findings from climate projections by 2100 using dynamic downscaling forced by CMIP3 and CMIP5 models for various SRES and RCP scenarios, respectively, estimate an increase in dry spells in tropical South America (east of the Andes), and in warm days and nights in most of South America. For the Amazon basin there is mixed conclusions and they have varied over time, some authors conclude that no systematic unidirectional long-term trend toward dries or wetter condition can be identified since 1920 (Magrin et al., 2014).

The studies developed specifically for Ecuador are highlighted, which are only a few. Buytaert et al. (2009) assessed the impacts of climate change on water resources in the Paute River. In this study which used an ensemble of 20 GCM run under the IPCC A1B scenario, final average monthly discharge projections by 2030 range from 23% to 518% of the current conditions, while the 10^{th} and 90^{th} quantiles are respectively 70% and 148% of the current conditions. In a following study, Buytaert et al. (2010), investigates the Tomebamba sub-basin of the Paute river basin, which hosts the largest hydropower dam in the country (Daniel Palacios, 1,075 MW). The study uses the RCM PRECIS to analyse the rainfall patterns and discusses the limitations of using GCM and RCM at the local level. The authors state that: *"resolving high-resolution precipitation gradients in climate models is difficult and potentially risky. Misalignments between simulated and the observed atmospheric processes may result in very poor performance of the regional climate model in certain locations"*.

Buytaert et al. also mention that since assuming future changes implies irreducible uncertainties about the direction and timing of these changes, adaptive management approaches to move away from a "predict-and-control" paradigm, towards a more adaptive approach, with continuous learning and flexibility is a key aim. This is of particular relevance for hydropower systems that have high infrastructural investments (irreversible decisions), which prevent continuous learning and adjustment. Therefore, diversification of strategies that can be flexibly applied when needed would suit energy planners the best. In a following study, Buytaert et al. (2011) also mention that in most humid tropical high-altitude regions, such as the Andes in Colombia and Ecuador, the production of glacier runoff is minimal and only locally significant, thus the driver of river discharge relies mainly on precipitation.

Vuille (2013) also studies climate change and water resources in the Tropical Andes (Ecuador, Colombia, Peru and Bolivia). According to this study, temperature increased by about 0.7 °C between 1939 and 2006, although this depends on elevation and slope of the region. Regarding precipitation, trends are weaker and much less coherent, due to characteristics of Andean topography. There are also far fewer high quality stations with long-term precipitation series, which makes the assessment of long-term precipitation very challenging.

Vuille also details glacier retreat in the volcanoes Antisana, Chimborazo and Cotopaxi in Ecuador. In a future scenario where glaciers continue to retreat and eventually disappear entirely, at least from lower-elevation catchments, it is logical to assume that the runoff behaviour will gradually transition from a situation with continuous water supply to one with most of the runoff concentrated in the wet season and with little to no base flow during the dry season. However, in countries such as Ecuador or Colombia, on the other hand – where glaciers are very small, the climate is much more humid, and precipitation is more equally distributed throughout the year – these changes in glacier hydrology are likely not very relevant on a larger scale. In addition, these countries benefit from an important buffering capacity of tropical wetlands. The study of Vuille also mentions the uncertainty that El Niño-Southern Oscillation (ENSO) brings to the region. During this event, the warm surface waters off the coast of Ecuador (and Peru) often cause torrential downpours over the coastal deserts.

The procedure detailed in this literature review regarding the impacts of climate change on hydropower should be understood as a *ceteris paribus* analysis, since several factors may affect the climatic change impact-hydroelectricity relationship (e.g. changes in land use, different uses of water, different energy scenarios, etc.). Several of these factors can be difficult to quantify and project, which can significantly increase the high degree of uncertainty inherent in this type of study, as well as obfuscate the impact of "pure" climatic effects. Nevertheless, the relevance of these factors should be kept in mind and their understanding of their interaction with hydroelectric generation and their vulnerability to global climate change should be understood.

2.3 ADDRESSING UNCERTAINTY

Regardless of the modelling paradigm, type of model or care taken to build models, uncertainty still remains. In this section, approaches used to deal with uncertainty are briefly discussed focusing on technics in climate change impacts assessments and energy system modelling.

2.3.1 *Uncertainty in climate change impact assessments*

In last decades, uncertainty has played a prominent role in global environmental change research, including climate change science and climate change impact science. The IPCC AR5 (IPCC, 2014b) defines uncertainty as *"a lack of complete information, as well as incomplete knowledge or disagreement on what is known and knowable."* Uncertainties in climate change impact studies on water resource endowment result from the natural complexity and variability of the hydrological system and its underlying processes, and from limitations on how these are implemented in models.

Much work has been done on hydrological uncertainty (see the review by Nearing et al., 2016) and uncertainty in climate change impact on water resources (see review by Kundzewicz et al., 2018). In these studies, it is stated that when using projections uncertainties, uncertainties mainly arise due to:

1. Scenarios of future socio-economic development,
2. GHG emission and sequestration scenarios,
3. GCMs,
4. RCMs or statistical downscaling methods,
5. Choice of the bias correction method (if applied),
6. Input data for hydrological model(s),
7. Hydrological model(s) structure(s), and
8. Parameterisation of hydrological model(s).

Basically, uncertainties appear in all the steps taking part in the climate change impact on water resources modelling chain that was presented earlier in Figure 2.1 on page 36.

The uncertainty in hydrological impacts modelling starts from the unknowns about the the development pathways of society. Future socio-economic driving factors (population, economic development, life conditions, technological advancements) is largely unknowable, and cannot be assigned objective probabilities. For example, Buytaert and Bièvre (2012) study the impact of climate change and demographic growth in the Tropical Andes, namely in four capital cities: Quito, Bogota, Lima and La Paz. The study shows that different assumptions about population growth have clear effects on water stress projections, even greater than those than climate change can cause in the mid-term (2050). The use of more efficient technologies and water recycling can help decrease overall water demand. The cooling technologies for thermoelectric generation and irrigation of bioenergy crops are among the most influential factors affecting future water demand in the context of climate change mitigation (Mouratiadou et al., 2016).

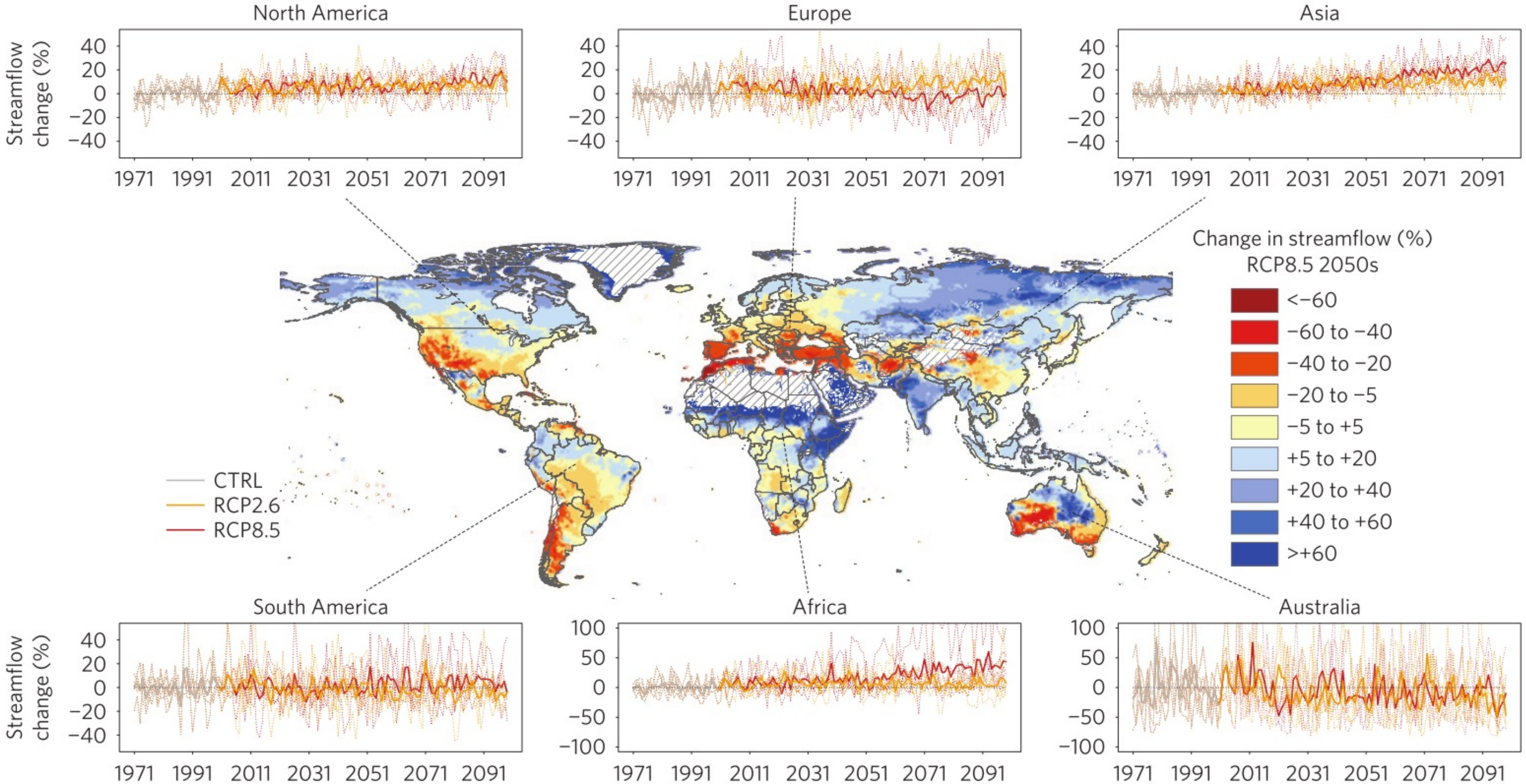
Results obtained by using different scenarios and different climate models (GCMs) can also be a large source of uncertainty. Intra-model uncertainty of projections (for the same GCM model and different emission scenarios) can be lower than the inter-model uncertainty (for the same emission scenario and different GCM models). In previous studies, only one GCM or one emission scenario output was used, whereas in recent studies, ensembles of several climate models have been used to map uncertainty. In addition to the selection of GCMs, the downscaling technique (statistical or dynamic) can explain a major portion of differences in reported projections (Vetter et al., 2017). A statistical bias correction is often carried out in order to render the model output closer to observation data in the reference period. Chen et al. (2013) applied and compared downscaling methods by using six statistical methods and two dynamic RCMs' data (precipitation and temperature) for two North American river basins. The authors concluded that comparing the uncertainty envelope of statistical downscaling methods to the envelope resulting from four RCM simulations indicates that both are similar, even though the latter was slightly larger for some statistics. Observations that are used to compare simulated values, can also be subject to errors, depending on location, the variables in question, and measuring practices and changes over time (e.g. new instruments, relocation of instruments, or drastic changes in the surroundings).

There are regions in the world where climate models of the current generation do not agree on the sign of future precipitation change. This means that projections of precipitation – the principal meteorological input signal to hydrological systems and to estimate streamflow – resulting from various climate models can be largely different. The study of van Vliet et al. (2016a) use a physical hydrological model to estimate streamflow by the end of the century and account for uncertainties by performing calculations for five individual GCM experiments as well as for the ensemble mean under the RCP2.6 and RCP8.5 concentration scenarios. Their results can be seen in Figure 2.4 on the next

page, which shows how the ensemble mean of GCM projections masks much wider uncertainty registered by individual GCMs.

The results of the study of van Vliet et al. show consistent increases in annual mean streamflow for high-latitude regions (northern North America, northern Asia), and large parts of the tropics (central Africa, southern Asia;). According to this study, for South America and Australia, the GCM-ensemble mean changes show still small reductions in mean annual hydropower usable capacity. However, the range indicating the uncertainties in hydropower capacity among the different GCM experiments is largest in both regions and shows both negative and positive signals of change (Figure 2.4 on the facing page). Uncertainty surrounding the sign of change in precipitation and consequently streamflow poses a challenge for many real-world applications in water sector management and infrastructure planning, such as for hydropower.

Figure 2.4: Impacts of climate change on annual mean streamflow



Note: Maps of changes in streamflow relative to the control period 1971–2000. Trends in changes for 1971–2099 are presented based on the GCM-ensemble mean results (thick lines) and for the five individual GCMs separately (thin dotted lines) for both RCP2.6 (orange) and RCP8.5 (red).
Source: van Vliet et al. (2016a)

Hydrological models are an additional source of uncertainty. Some authors suggest to use the best performing hydrological models only and disregard the poor performing ones, depending on their ability to reproduce historic variables of particular interest for the problem at hand and the area of concern. Nevertheless, some experts (Krysanova et al., 2017, 2018), advocate the necessity of using ensembles of all available hydrological models, rather than removing the models that do not perform sufficiently well in the calibration and verification stages. Cornelissen et al. (2013) compare discharge results for a group of four different physical and conceptual models for the Térou Catchment in Benin, West Africa. They conclude that if hydrological models are applied within a single study, model calibration often results in reliable simulations of the past; however, the influence of model choice and model calibration on the simulation of climate change impacts remains unclear.

So, at the end of the day, *what is the main source of uncertainty in the hydrological impact modelling chain?* and *how can we reduce its uncertainty?*

Although there are uncertainties in all the stages of a study of climate change impacts on water resources, studies have identified that the greatest uncertainty is associated with GCM projections for different GHG concentration scenarios (Graham et al., 2007; Bates et al., 2008; Kundzewicz et al., 2018). In a most recent study, Hattermann et al. (2018) use an analysis of variance (ANOVA) approach to allocate and quantify the main sources of uncertainty in the hydrological impact modelling chain. The authors compare results using a set of five GCMs and up to 13 hydrological models, for nine large scale river basins across the globe (including the Amazon), under four emissions scenarios. Their results show that GCM uncertainty in projected precipitation trends obscure all other sources of uncertainty in the modelling chain. An additional finding is that the contribution of GCM related uncertainty is highest in periods of the year, and in regions, where precipitation dominates the river flow regime, such as in basins like the Amazon, Blue Nile and Ganges. In comparison, hydrological model uncertainty is higher in periods of the year, and regions, where snow melt, soil freezing processes and evapotranspiration have a substantial influence in river regime, for example in the sub-arctic climate of the Lena river (Russia). GCM-driven uncertainty relative to the total uncertainty has a dominating influence, which has also been reported by e.g. Eisner et al. (2017), Vetter et al. (2017), and Buda et al. (2017), all using hydrological models in regional climate change impact assessments.

Kundzewicz et al. (2018) suggests a general framework for reducing uncertainty assessment of climate change impact on water resources based in three areas: i) data and information, ii) hydrological models, and iii) climate models. Data and information uncertainty (resulting from incomplete or un-precise information) may be reduced by obtaining more exact information (conducting additional observations or measurements, etc). Maintaining and extending meteorological and hydrological observation networks can also help populate global datasets of basic data needed for modelling impacts. To reduce the uncertainty of results when using a hydrological model, calibration and validation of the model should be done before applying it for climate change impact assessment. The calibration and validation procedure should include several statistical goodness-of-fit criteria (e.g. Nash and Sutcliffe efficiency, percent bias, residual variation, and coefficient of determination) (Thompson et al., 2013).

Regarding climate model and impact models, the current approach to reducing (or rather assessing) uncertainties is to perform studies where the output of several climate models is used as input to several hydrological models to produce an ensemble of potential changes (scenario analysis). The range of projections (spread of model outcomes) is used as a proxy measure of uncertainty and the mean of the ensemble of model projections (e.g. CMIP5) is often advocated as a useful representation of the future. The underlying assumption is that the greater the number of models in agreement, the stronger the robustness of the climate projection. This clearly has shortcomings, Kundzewicz et al. (2018) states that the ultimate quality index of a hydrological model is the difference between model outputs and reality, which is often unknown or can even be unknowable when looking into the future impacts of climate change.

The combination of GCMs and GHG emission scenarios has been used to assess uncertainty in studies about climate change impacts on hydropower. This has been detailed for a group of selected studies in Table 2.6 on page 59. Some studies capture only uncertainty for the emission scenario (intra-model uncertainty), given that they only use one GCM and compare impacts with different emission scenarios. For instance, the studies by McPhee et al. (2012) and De Lucena et al. (2009) used the SRES A2 and B2 scenarios and only the HadCM3 GCM for hydropower studies in Chile and Brazil, respectively. Escobar et al. (2011) assessed hydropower generation in Latin America and the Caribbean drawing on projections of average temperature and rainfall throughout the current century, also for the SRES A2 and B2 emission scenarios and used the ensemble mean value of the CMIP3 GCM results. In contrast, the studies of Grijsen (2014) for Cameroon and Golombek et al. (2012) for Western Europe use only one emission scenario – the SRES A1B –[27] and several GCMs (between 15 and 20), thus rather capturing only inter-model uncertainty surrounding GCM projections.

27 The SRES A1B emission scenarios is considered as a middle-of-the-road scenario with balanced technological development

To consider a broader range of uncertainty, more recent studies consider multiple emission scenarios and GCMs. Shrestha et al. (2016) consider the more recent RCP4.5 and RCP8.5 with three GCMs (MIROC-ESM, MRI-CGCM3, and MPI-ESM-M) to assess risk due to climate change for a hydropower project in Nepal. These studies, among others (e.g. Hamlet et al., 2010; Seljom et al., 2011; Spalding-Fecher et al., 2017), highlight the significant sensitivity that hydropower can have to precipitation changes and that the main source of uncertainty for regional climate scenarios is associated with projections of different GCMs, therefore the importance of using several GCMs to assess uncertainty and the growing interest in using large ensembles of GCMs to improve the reliability of future projections.

Climate models still need to be improved before they can be effectively used for adaptation planning and design (Kundzewicz et al., 2018). Substantial reduction of the uncertainty range would require using finer resolution of GCMs and RCM, but overall improving the understanding of the processes implemented in climate models. However, according to Buytaert et al. (2010), GCM uncertainties are unlikely to be eliminated or substantially reduced in the near future.

2.3.2 *Uncertainty in energy system modelling*

The long-term future transition of the energy system is shaped by a combination of factors that are deeply uncertain, including technology innovation, resource availability, and socio-economic dynamics (Decarolis et al., 2017). As stated by Awerbuch and Yang (2007), the motivation for studying uncertainty in energy planning takes relevance due to a *change of era* – from a regulated and stable energy market to a more competitive and uncertain environment. Mirakyan and De Guio (2015) agree with this latter, but also pose that uncertainties in the power sector are also created by the scarcity of fossil energy resources, climate change, increasing environmental restrictions and the resulting high share of intermittent energy resources, such as wind and solar PV energy.

Given such deep uncertainties about the future, singular energy system model projections obscure the full spectrum of possible energy system futures. The focus of energy system model-based analysis should thus be based on producing insights, which requires the identification of patterns across model runs under uncertainty. Two types of uncertainties can be distinguished for energy system models: *parametric* and *structural* (Kesicki, 2012). Table 2.7 summarises the definition of these two types of uncertainty and ways to treat them. Joode and Boots (2005), Vithayasrichareon (2012) and Decarolis et al. (2017) present approaches for dealing with uncertainty in energy system models

Table 2.7: Types of uncertainty in energy system modelling

Type	Definition	Treatment of uncertainty
Parametric	Uncertainty about the appropriate input parameters to use, e.g. demand forecasts, investor risk level, weather data.	• Scenario and sensitivity analysis • Stochastic programming • Near optimality: Modelling to generate alternatives • Probabilistic approach: Monte Carlo simulation/portfolio theory
Structural	How the model itself relates to the real-world process it is modelling, e.g. what effect does this simplifying assumption have on the results?	• Scenario and sensitivity analysis • Multi-model comparison • Near optimality: Modelling to generate alternatives • Historical data • Expert opinion on the shortfalls of the model • Experimentation

that address both parametric and structural uncertainty, of which the main approaches to deal parametric uncertainties are further explained in the following paragraphs.

2.3.2.1 *Scenario and sensitivity analysis*

Scenario analysis has appeared as a means of characterising the future energy pathway and its uncertainties through a structured and imaginative process (Rounsevell and Metzger, 2010). Such as Wilson (2000) states, *"scenarios help explore the what, how and/or if in future pathways and allow to understand how different key driving forces might lead to different outcomes."* Scenarios are not predictions or forecasts but rather are a collection of possible futures that establish the boundaries of uncertainty and the limits within plausible futures (Fortes et al., 2014a). In a secondary stage of use, scenarios can be considered as a management tool used to improve the quality of executive decision making (Bradfield et al., 2005). Because of this broad use, a wide range of scenario methodologies and classifications have emerged, as indicated by the extensive scenario planning literature (van Notten et al., 2003; Bradfield et al., 2005; Börjeson et al., 2006; Wilkinson and Eidinow, 2008).

Scenario analysis can be used to address parametric uncertainty by translating scenario assumptions into energy system model input parameters, and it can address structural uncertainty by altering the model formulation to address an uncertain scenario element. While scenarios analysis wishes to explore plausible outcomes of a system, drawing different scenarios does not constrain uncertainty and there is actually no way of knowing whether the scenario process has been successful for this. Except for waiting and at some point in the future assess scenarios in hindcast to see which ones approximated reality. The more complex the system (and therefore the higher number of variables to be projected), as is the case of the energy system, and the further into the future the scenarios reach, the more likely it is that they will not cover all plausible futures and fail to capture the actual evolution of the system. The study of Trutnevyte et al. (2016), for example, performs a retrospective analysis of twelve UK energy scenarios developed between 1978 and 2002. The study argues that a greater reflection is needed on structural uncertainties, rather than on parametric uncertainties, i.e. on the ability of the model to capture the actual "behaviour" of the energy system, including aspects such as governance.

To quantify uncertainty and risk in scenarios, sensitivity analysis proposes the change of the uncertain variables within a range of values to address parametric uncertainty by identifying the model input parameters that have the largest influence on the modelling results. Uncertain parameter values are varied one at a time to identify the value of a parameter on the final output (usually in %). Though this is a fairly easy approach that can give insight on which the key uncertain parameters are, it is not likely to be sufficient when there are a number of interacting uncertainties (Awerbuch and Berger, 2003). Usher and Strachan (2012) argue that applying a deterministic methodology to a complex and multi-faceted area of strategy development that is inherently uncertain is problematic and that there is a need to move beyond sensitivity analysis when considering parametric uncertainties. They highlight three key problems with simple sensitivity analysis: i) the probability of an input value cannot be quantified, ii) disparate sensitivity scenarios make policy insights more difficult to determine, and iii) the cost of uncertainty (i.e. risk) is unknown.

Sensitivity analysis can also be used to test a models structural uncertainty. Alternative model formulations (e.g., more or less time slices or regions, inclusion or exclusion of the transmission system, etc.) can be used to understand the sensitivity of model results to these variations in model structure. Sensitivity analysis applied in this way can help extract insights that are robust to different model formulations and help navigate what model formulation require more attention and detail (Decarolis et al., 2017). In addition, multi-model exercises that explore the same future scenarios can be used to identify structural uncertainties across models, as for example in the studies of Lucena et al. (2018) for energy system models and Vetter et al. (2015) for hydrological models.

Global sensitivity analysis is an approach to address parametric uncertainty by identifying the model input parameters that have the largest influence on the modelling results. This type of sensitivity analysis can be performed simultaneously for a combination of input parameters that can be correlated by assigning a series of predefined probability distributions or ranges to the uncertainty parameters. The results of applying global sensitivity analysis to an energy system optimisation model can provide a ranking of inputs by importance i.e. the input parameters which uncertainties impact the model results the most and therefore screen out unimportant parameters from a scenario analysis. Examples of studies using global uncertainty analysis in an energy system optimisation model (UK TIMES model) is that of Fais et al. (2016) and on a multi-model comparison of integrated assessment models that of Marangoni et al. (2017)

2.3.2.2 *Stochastic analysis*

A limitation of energy system models is that an individual scenario assumes all uncertainty are resolved *ex ante*, i.e. all parameters are assigned values prior to the model run. However, decision makers need to take action before uncertainty is resolved (Decarolis et al., 2017). Stochastic optimisation can address this limitation by explicitly considering uncertainty within the model formulation. In this approach uncertain variables are modelled by Markov chains or simple event trees, referred as stochastic programming (Labriet et al., 2015; Mirakyan and De Guio, 2015). The formulation of stochastic programming methods, however, is rather complex due to the long planning horizon of the sector, and still depends largely on a decision tree methodology, where each branch in the tree is assigned an outcome and an associated probability. Optimising over a finite set of future outcomes encoded within the event tree yields a near-term hedging strategy that accounts for potential future outcomes and puts the decision maker in a position to take recourse action as uncertainty is resolved.

Hu and Hobbs (2010) give an overview of stochastic analysis and use a stochastic feature of the MARKAL energy optimisation model (stochastic MARKAL) applied to the US electricity sector to examine uncertain CO_2 mitigation, natural gas prices and electricity demand growth under multi-pollutant policies. An additional example is the study of Seljom and Tomasgard (2015), in which the intermittent characteristics of wind power are modelled as a stochastic parameter in a TIMES model of the Danish heat and electricity sector. Further examples of stochastic programming applied to energy system optimisation models can be found in the studies of Babonneau et al. (2012); Loulou and Labriet (2008); Loulou and Kanudia (1999); Kanudia and Loulou (1998).

An identified limitation of stochastic analysis applied to energy planning, is noted by Usher and Strachan (2012) as the 'curse of dimensionality', whereby the problem size increases faster than the number of dimensions added, quickly resulting in computationally intractable problems. For example, the limitation of stochastic MARKAL to nine probable States-of-the-World (SOW) means that the analysis is limited to specifying one uncertain variable with up to nine discrete future values, two uncertain variables each with three discrete future values, three uncertain variables each with two discrete future values (and a limited number of other permutations). In the case of addressing more than nine possible futures, this method increases dramatically in complexity.

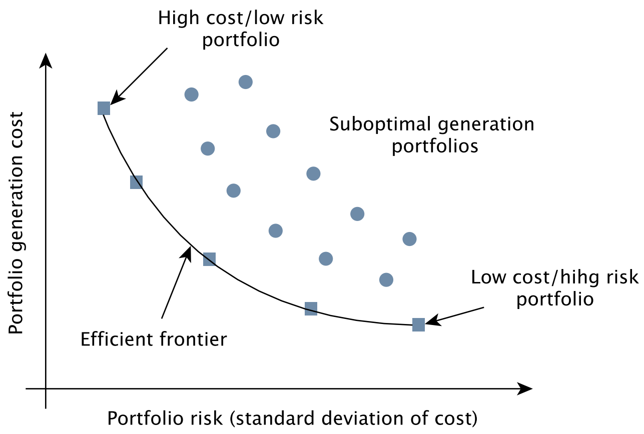
2.3.2.3 *Generating near optimal solutions*

In an energy system optimisation context, the technique called 'modelling to generate alternatives' (MGA) means finding alternative solutions that are close to the minimum cost or maximum welfare but utilise a different set of technologies to meet end-use demands. The objective function of the model is modified in order to explore alternative solutions that are near optimal in solution space but very different in decision space (Decarolis et al., 2017). The application of MGA represents a simple way to explore structural uncertainties in the model.

Examples of studies that use near-optimal approaches are that of Trutnevyte (2016) that uses MGA to model retrospectively the real-world UK electricity system transition (1990–2014). In an additional study at the global scale, Price and Keppo (2017) have developed a formulation of the MGA objective function and have integrated this into a TIMES integrated assessment model (TIAM) to maximise the difference associated with the consumption of each primary energy commodity between successive iterations. Finally, Li and Trutnevyte (2017) combined Monte Carlo simulation with MGA to produce 800 different scenario pathways in order to explore UK electric sector transition pathways to 2050.

As Decarolis et al. (2017) points out – *"No optimisation can fully capture real world complexity; unmodelled objectives and constraints are always present."* Thus, decision makers may find that the near optimal solutions are preferable to the base solution when their own preferences and concerns – exogenous to the model – are brought to bear on the model solutions. In contrast to, stochastic optimisation, which explicitly incorporates uncertainty into a single run to help inform a decision strategy, MGA yields a set of computer-generated alternatives. The intent of MGA is not to provide a singular an-

Figure 2.5: Efficient frontier for electricity generation portfolios



swer, but rather to provide a set of alternative solutions that indicate the degree of flexibility in the model solution and can be further evaluated. The idea to not offer a single least-cost answer but give a range of options to the policy maker according to his/her preferences is key to understand the next method to treat uncertainties, which is one of the focus of this thesis.

2.3.2.4 *Portfolio-based analysis*

Financial *portfolio theory* is based on the research of Nobel Laureate Harry Markowitz (Markowitz, 1952) and has been often applied in the context of financial portfolio to estimate investment return and expected portfolio risk on a year-to-year basis (Fabozzi et al., 2009). The main insight of portfolio theory is that the value of each asset in an investment portfolio can only be determined relative to the impact that the risk of each asset has on the portfolio. This applied to the energy planning process would indicate that it is necessary to evaluate each generation technology according to the impact it has on the overall generation cost and risk of the electricity generation portfolio[28], rather than only evaluating generation cost on a stand-alone basis. As pointed out by the seminal study of Awerbuch and Berger (2003) who applied portfolio theory to the power sector – *"energy planning therefore needs to focus less on finding the single lowest cost technology alternative and more on developing efficient (i.e. optimal) generating portfolios."* Efficiency from this point of view relates to generation portfolios that minimise risk for an expected level of cost or minimise cost for an expected amount of risk (Jansen et al., 2006).

28 Generation portfolio is understood as the collection of all the technologies that contribute with the generation of electricity in a power system.

To exemplify this concept, Figure 2.5 on the preceding page shows an efficient frontier curve (i.e. the trade-off between cost and risk) and a number of different generation portfolios with different cost and risk profiles. With this approach, optimal generation portfolios fall along the efficient frontier (represented by squares) where costs can only be reduced by accepting higher cost risks amongst the possible generation portfolios (Pareto efficiency[29]). Generation portfolios that are not on the efficient frontier (represented by circles) are considered suboptimal, either because their expected generation costs are too high relative to the cost risks or the cost risks are too high relative to the expected cost. From a societal perspective, the most desirable generation portfolio is the one which results in the lowest expected cost within some level of acceptable risk (Jansen et al., 2006). The mathematical formulation of portfolio theory will be discussed in further detail in the following chapter in Section 3.3 on page 159.

Portfolio based analysis with the efficient frontier technique also serves as a mean for decision-makers to select a set of efficient generation portfolios that suit particular cost-risk preferences. These preferences can be highly complex and involve tradeoffs between, for example, up-front and on-going fuel costs. With increasing uncertainty in the electricity industry, portfolio-based analysis is well suited for evaluating capacity expansion strategies since this approach can help exploring options that enhance energy diversity, security, and environmental sustainability. The most important aspect of portfolio theory is that proper diversification of assets in a portfolio can strongly reduce total portfolio risk (Rubinstein, 2002).

There is a growing body of literature which has applied portfolio theory to electricity system planning techniques to account for risk and uncertainty. Table 2.8 on page 82 presents a list of reviewed studies that use portfolio theory for electricity planning. An examination of the literature shows that there is no single approach to defining the type of efficient frontier curves. Studies based on both economic and electricity generation criteria can both be found. Economic studies present many return-risk frontiers, as well as cost-risk frontiers. The definition of return is equally diverse, having been defined in earlier studies as: the reverse of the cost of generation (kWh/$) (Awerbuch and Berger, 2003; Awerbuch and Yang, 2007), the Net Present Value (NPV) for the technology of generation (Roques et al., 2008; Westner and Madlener, 2011), the Internal Rate of Return (IRR) Muñoz et al. (2009), and as the relative measure of environmental efficiency (Hadian and Madani, 2014). On the other hand, studies based on electricity generation

29 Pareto efficiency or Pareto optimality is a state of allocation of resources from which it is impossible to reallocate so as to make any one individual or preference criterion better off without making at least one individual or preference criterion worse off.

criteria (Roques et al., 2010) have used the expected levelised cost of electricity (LCOE) as a reference ($/kWh).

The models to solve portfolio theory include varied optimisation functions and constraints, and the majority of them consider different horizons and countries. Some studies look to maximise utility while constraining the maximum generation technology shares (Awerbuch and Berger, 2003; Roques et al., 2008; Arnesano et al., 2012; Losekann et al., 2013), while others, in contrast, seek to minimise cost while constraining risk (Grubler and Fuss, 2012; Nijs and Poncelet, 2016) , or even minimise cost and risk simultaneously (Allan et al., 2011; Delarue et al., 2011).

Most studies have used portfolio theory to make a case for reducing risk through diversified generation portfolios. For example, Roques et al. (2008) use portfolio theory to identify optimal generation portfolios in the UK, taking into consideration fuel and also CO_2 price risks and their degree of correlation. Zhu and Fan (2010) apply portfolio theory to evaluate China's 2020 medium-term plans for capacity expansion, concluding that nuclear and renewable-power can reduce generation portfolio risk. Allan et al. (2011) use a portfolio selection approach applied to the regional electricity generation mix in Scotland in 2020 and show that marine and tidal renewables can contribute to lower risk electricity portfolio without increasing system cost. Vithayasrichareon et al. (2015) study how the uptake of solar PV and wind can hedge risk against volatile coal prices in the Australian energy market.

An identified limitation of the application of portfolio theory to electricity planning is that it is used as a *static ex post* tool – it only assesses the performance of generation portfolios in a horizon year, without taking into account the dynamic and multi-stage process of generation planning and investment. Portfolio risk is calculated for bespoken generation prices and risk profiles in the future, in other words, the portfolio assessment is performed exogenously from the energy system model optimisation process. Allan et al. reaffirm the idea of substantial scope of research for combining the portfolio selection approach with other energy system models, in an attempt to determine whether apparent 'no regret' policies really are feasible. This is due to the fact that portfolio theory models work with exogenous generation scenarios and cannot assess the technical feasibility of a portfolio per se. Ferreira and Cunha (2012) in a study for the Portuguese power system recognise that portfolio theory for electricity system analysis must go beyond the traditional models, where future work should envisage the development of new models combining portfolio theory with generation expansion models for electricity power planning. Vithayasrichareon (2012) similarly states that future research should lead in the implementation of dynamic portfolio applications that integrate it in multi-period (multi-horizon) power system investment analysis.

Some critics of the application of portfolio theory to the generation of electricity assets can be found in the literature. Stirling (2010) criticises the application of portfolio theory in such diverse assets as those of the power sector. The line of thought of Stirling is that this approach does not include the totality of the risk elements that are being analysed in a real asset (which go beyond the historic volatilities and correlations between the assets). Among them would be the security of supply or the reliability of the systems during times of high demand. However, a precise definition of restrictions and the objective functions in the model can partially resolve this problem, such as the studies of Delarue et al. (2011) and Vithayasrichareon et al. (2015) that include ramp rate limitations of generation technologies and the volatility of electricity demand. Other authors (Krey and Zweifel, 2008; Awerbuch et al., 2006; Li and Trutnevyte, 2017) focus their questions on the high level of ignorance that characterises the energy context. Thus the exclusive use of historical data (fossil fuel prices and electricity generation component costs) is limiting and can only result in obtaining non-reliable results — what happens in the past does not necessarily inform the future.

These gaps could be overcome by a novel combination of an energy systems optimisation model that could integrate concepts of portfolio theory. An energy system optimisation model could address the problems of dealing only with static forecasts of technology generation prices, as well as with issues regarding the operation of the system in time. It can also handle a much broader amount of technologies that can better depict the context dependent characteristics of a country. In addition, the benefit of using an integrated energy system optimisation model is that it accounts for the full cost of the system, such as costs related to capacity credits and back up generation for intermittent renewable resources. It also captures the interaction of energy generation and conversion technologies on both the supply and demand side. The early study of Messner et al. (1996), showed an initial attempt to introduce an risk factor in the optimisation function of the energy system model MESSAGE III, considering however only eight power sector technologies and not including the uncertainties of fossil fuel prices. The methodology of this study was revived (and extended) by Krey and Riahi (2009), who similarly used a global MESSAGE model with an integration of a risk parameter in the objective function and included the uncertainties of fossil fuel prices. However, this study used theoretical measures of uncertainty not based in actual uncertainty data of technologies and volatility of oil prices. Most recently, an application of portfolio theory into an energy system optimisation model (TIMES) was recently conducted by Nijs and

Poncelet (2016). These authors assessed the risk reduction potential of renewable energy with a case study for the Belgian power system up to 2040 and consider only the volatility of coal and natural gas prices. However, there are no studies using portfolio theory integrated into an energy system optimisation model that also consider uncertainty of capital costs, which could be a relevant area of study for countries depending on and willing to expand capital intensive large hydropower infrastructure.

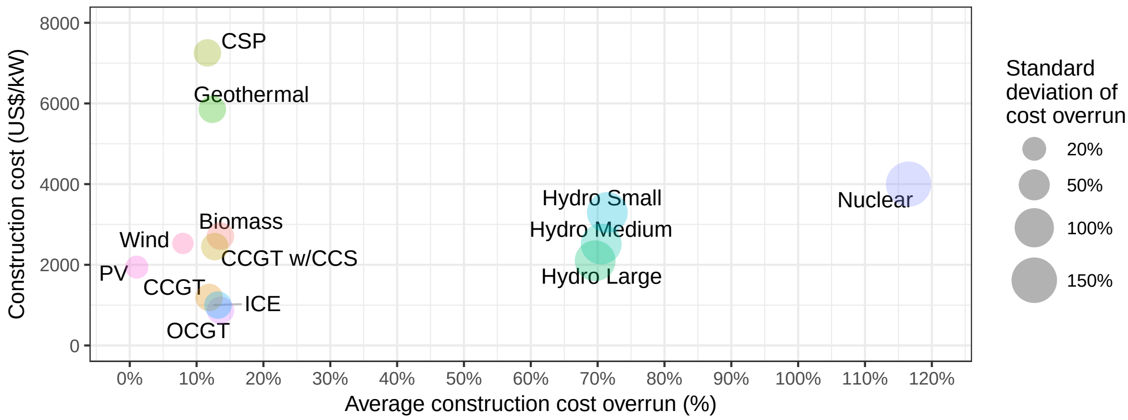
Table 2.8: Reviewed studies that use portfolio theory for power sector planning

Author	Objective functions	Constraints	Uncertainties considered	Horizons	Country/region
Awerbuch and Berger (2003)	Utility maximisation	Technology limit shares	Cost components of generation technologies and fuel prices	2000 & 2010	EU
Jansen et al. (2006)	Risk and cost minimisation	Technology limit shares	Cost components of generation technologies	2030	The Netherlands
Mcloughlin and Bazilian (2006)	Risk and cost minimisation	Technology limit shares	Natural gas prices, carbon prices, LCOE of generation technologies	2020	Ireland
Awerbuch and Yang (2007)	Risk and cost minimisation	Technology limit shares	Cost components of generation technologies , fuel and CO2 prices	2020	EU
Roques et al. (2008)	Utility maximisation	Inexistent	LCOE of gas, coal and nuclear plants	-	UK
Zhu and Fan (2010)	Risk minimisation	Technology limit shares	LCOE of generation technologies, fuel and CO2 price risk.	2020	China
Allan et al. (2011)	Risk and cost minimisation	Technology limit shares	LCOE of generation technologies	2020	Scotland
Delarue et al. (2011)	Risk and cost minimisation	Technology production ramp rates	LCOE of generation technologies and wind power variability	-	Belgium
Vithayasrichareon and MacGill (2012)	Cost minimisation	Installed capacity related to demand side	Future fossil- fuel prices, carbon pricing policies, electricity demand, and capital costs of generation technologies.	2030	Thailand
Ferreira and Cunha (2012)	Renewable energy share maximisation	Renewable energy share variability	Hourly data of wind, hydro and solar plants	2022	Portugal
Bhattacharya and Kojima (2012)	Risk minimisation	Technology limit shares	LCOE of generation technologies	-	Japan
Grubler and Fuss (2012)	Cost minimisation	Risk premium	Technology availability, cost and carbon prices	2050	Global

Table 2.8 (continued): Reviewed studies that use portfolio theory for power sector planning

Author	Objective functions	Constraints	Uncertainties considered	Horizons	Country/region
Arnesano et al. (2012)	Utility maximisation	Technology limit shares	Cost components of generation technologies , fuel, CO2 prices and availability of renewables	2009 & 2020 & 2030	Italy
Lemos and Botero (2012)	Volatility minimisation	Level of the LCOE	Cost components of hydropower and thermoelectric (gas and coal)	2005&2019	Colombia
Losekann et al. (2013)	Utility maximisation	Technology limit shares and CO2 prices scenarios	Fuel costs, capital and O&M of generation technologies, CO2 price	2020	Brazil
Hadian and Madani (2014)	Efficiency maximisation	Resource use efficiency	Cost, carbon foot print, water footprint and land footprint	-	-
De-Llano Paz et al. (2014)	Risk minimisation	Technology limit shares	Generation cost components and environmental externalities	2020	EU-27
Matosovi and Tomši (2014)	Risk minimisation	Inexistent	Intermittency of renewable energy sources and accuracy in the day-ahead forecast		
Vithayasrichareon et al. (2015)	Cost minimisation	Installed capacity related to demand side	Gas prices, capital cost of generation technologies, carbon pricing policy and electricity demand	2030	Australia
Nijs and Poncelet (2016)	Cost minimisation balanced by risk	Risk level and energy system model constraints	Oil and coal prices	2014 – 2040	Belgium

Figure 2.6: Average cost escalation and volatility of cost overruns for electricity infrastructure projects.



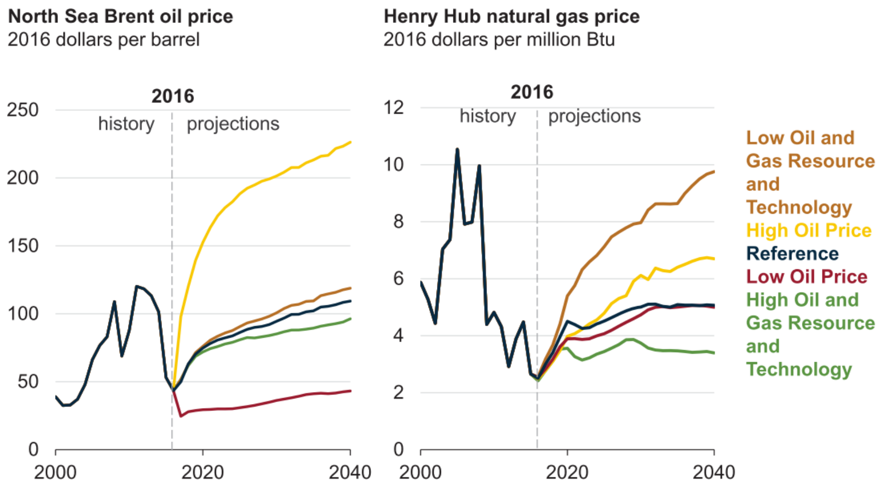
Source: based on Sovacool et al. (2014a)

2.3.2.5 *Technology cost and price uncertainty*

Regarding the scope of this thesis, capital cost of electricity generation infrastructure is an important parameter considered by energy system optimisation models to inform energy planners in the design of reliable, secure and least-cost electricity investment portfolios. All electricity generation projects can be susceptible to cost overruns; however research has identified hydropower as the technology with the second largest average cost overruns (after nuclear) and the longest mean construction times. Sovacool et al. (2014a), assessed construction cost overruns of 401 power plant projects developed between 1936 and 2014 in 57 countries. The analysis evidences hydropower as a generation technology that presents a high average cost escalation (70%) and volatility of cost overrun (cost standard deviation of 111%), as can be seen in Figure 2.6.

According to Sovacool et al. (2014a), one of the possible explanations for hydropower projects to portray the largest cost overruns is that they are, on average, more materials-intensive that other electricity generation technologies. The World Commission on Dams suggests that large hydropower projects are prone to unforeseen excavation and construction problems given the geotechnical conditions cannot be precisely determined until after the construction of the project begins (World Commission World Commission on Dams, 2000). A study by Flyvbjerg (2014) assessed the outcomes and costs of 186 hydropower dams – built between 1934 and 2007 in 65 countries. The study found *"overwhelming evidence that estimated budgets are systematically biased below actual costs of large hydropower dams"* and that *"actual costs were on average 96% higher than estimated budgets."* Awojobi and Jenkins (2016) found that *"greater complexity in terms of the size of the plant installed and the physical height of the dam are some of the origins of optimism bias and strategic parameters used to underestimate the cost of the projects."* Ansar et al. (2014) found

Figure 2.7: Crude oil and natural gas prices projections by 2040



Source: EIA (2017)

that nine out of ten dams suffered cost overruns in the past. Other previous studies confirmed the same trend in hydropower projects (Ansar et al., 2014; Sovacool et al., 2014a; Awojobi and Jenkins, 2015, 2016; Callegari et al., 2018). In addition, Locatelli et al. (2017) states that large hydropower projects are large unique projects where public actors play a key role and are very likely to be affected by corruption. According to Callegari et al. (2018) who assess cost overrun of hydropower projects in Brazil, corruption worsens both cost and time performances. An issue that can have important long-term development implications for Ecuador, South America and other regions where hydropower is the largest source of electricity generation.

Similarly, oil and gas prices are uncertain and volatile while they are one of the key parameters in the least-cost solution of energy system optimisation models. Due to the important role of oil in the world economy, there has been a large amount of research intended to capture the economic and financial consequences of changes in the price of oil and gas (Cunado et al., 2015; Diaz et al., 2016). Low prices of oil and gas is one of the barriers for the uptake of more efficient and low-emitting energy sources and conversion technologies. Energy system modellers usually work with price scenarios of oil and gas provided by international market reports (e.g. IEA, 2014b) and defining cost production curves for mining or importing of these resources. However, most price projections for the long-term are of linear trend and are set between deterministic scenario ranges. For example, Figure 2.7 shows five scenarios for oil (Brent) and natural gas (Henry Hub) prices by 2040 developed by the U.S. Energy Information Administration Annual Energy Outlook (EIA, 2017). While these scenarios depict the uncertainty range for fossil fuel commodity prices depending on future resource and technology levels, they clearly omit the volatility and uncertainty registered in the historic trend of prices (see price evolution from year 2000 to 2017 in Figure 2.7). Therefore, portraying oil and gas prices in an energy system model as a constant linear trend fails to represent reality and the impact that positive or negative changes in fossil fuel prices can have between periods of the modelling horizon.

2.4 CHAPTER SUMMARY

This chapter reviewed the current state-of-knowledge on the impact assessment of climate change on hydropower and the uncertainties to be taken into consideration when they are assessed with modelling tools. Several approaches were identified that can be applied to investigate different perspectives on how climate change impacts water resources and how in turn this affects long-term hydropower generation. Articles assessed in this literature review have provided a number of methodological details with respect to climate change models, hydrological models and energy models.

The literature review has revealed that GCMs are the main source of uncertainty for precipitation and thereof runoff projections (as shown in Section 2.2.1 on page 35). While a number of GCMs have projected positive precipitation increases for certain regions in the world, other studies have found negative values when using a different set of GCMs. A number of reasons can explain these range of results. For instance, the use of different GCMs with different levels of resolution and downscaling technics can lead to dissimilar results. In addition, the transfer of uncertainties in the modelling chain of climate change impacts on water resources can also explain contradicting results. As a result, the wide diversity of runoff projections makes it difficult to use past trends to plan long-term hydropower systems deployment.

Therefore, the first research question of this thesis aims at developing a climate change impact assessment on hydropower generation: **How broad is the uncertainty of hydro-climatic variables portrayed in a large ensemble of climate projections and the impact on the availability of runoff for hydropower generation?** Based on the literature review on uncertainty of climate change in Section 2.3.1 on page 66, it was found that most studies have worked with a discrete combination of only few GCM results to assess the uncertainty space of climate change. Thus, for this research a large ensemble of GCM models has been selected to parameterise uncertainty for future hydro-climatological conditions – as will be detailed in Section 3.1 on page 91.

In addition, although, the energy sector is vulnerable to climate change, the modelling of adaptation alternatives, their costs and benefits is seldom explored in the modelled adaptation literature, which constitutes a good area for research. Only a few studies have been found that go beyond climate impact assessment on hydropower generation and, with the aid of an energy system optimisation model, assess the energy system in its wholeness and propose least-cost adaptation/policy interventions to the threat of climate change on hydropower – see Section 2.2.2 on page 46. It should be mentioned that, previous studies that focus on the impact of climate change on hydropower using energy system optimisation models are few and have mainly focused in developed regions (e.g. Seljom et al. 2011; Teotonio et al. 2017; Kannan and Turton 2014; Lind et al. 2013). There are only few assessments for developing countries, such as for Brazil (Lucena et al., 2018) and for Ethiopia (van der Zwaan et al., 2018). When focusing on hydropower assessment, the analysis should capture the particularities of hydropower in terms of investment, potential, operation and vulnerabilities. This thesis aims to assess the representation of hydropower in a more comprehensive manner than it has carried out before within the energy system model. Issues such as its lumpy investments profile, remaining potential inventory, inter-annual operation characteristics, and capital cost overruns will be assessed. This is important in the sense that large hydropower projects can crowd out other technologies options available for the least-cost long-term expansion capacity plan, that although could cost more, could have lower risk profiles and be more robust to climate change impacts. This is of relevance for countries which are currently expecting to deploy large shares of hydropower capacity in their power systems.

Therefore the second research question reads: **How does hydropower output variations due to climate change impact the long-term least-cost power system development pathway of Ecuador by 2050?** As hydropower is dominant in Ecuador's power system and it is expected to remain as the main source of electricity during the following decades, an energy system optimisation model was selected in order to assess the impact of climate change in the power system and assess least-cost measures of adaptation – the justification for this decision is further discussed in Section 3.2 on page 110.

Regardless of the modelling paradigm, type of model or care taken to build models, uncertainties still remain. Uncertainty reflects the inability to estimate the exact value of a variable or comprehensively capture a relationship – see Section 2.3.2 on page 72. Given the long-term scope that climate change impact assessments demand, other uncertainties take relevance in such long periods of time. Prices of fossil fuels and technology costs are examples of modelling parameters that can change significantly in the future and in some cases their uncertainty will never be resolved, thus impacting the solution when using energy system optimisation models. Although there are many uncertainties in the process of energy scenario building (demography, economic development rate, technological uptake, energy demand, etc.), this thesis will focus on the uncertainties of fossil fuel and capital cost overruns of power technologies. The rationale behind this is that beside the operation characteristics of each generation technology, investment and operational costs of power technologies are the leading input parameters that inform the least-cost development plans of hydropower-dependant developing countries, and assessing their uncertainty can lead to different configurations of the least-cost power sector expansion pathway. Capital intensive hydropower is competing with other capital intensive non-hydropower renewables and with cheap conventional thermal plants. However, large hydropower has larger capital cost overrun probability than other non-hydro renewables and thermal generators, although these later are vulnerable to the price volatility of fossil fuels.

The third research question is stated as: **How does incorporating recurring uncertainties such as the volatility of fossil fuel prices and the capital cost of electricity infrastructure impact the investment portfolio for the power sector?** Financial portfolio theory is an approach well suited to give treatment to this kind of uncertainties in the power sector and to date, it has been mostly applied exogenous to the energy system model. Therefore portfolio theory will be integrated in the selected energy system optimisation process to assess how the least-cost power sector development pathway for Ecuador changes when risk is integrated into the optimisation process – this approach will be further discussed in Section 3.3 on page 159.

The modelling methods used to tackle each research question will be provided in the following chapter.

Part II

METHODOLOGY

3

METHODOLOGY

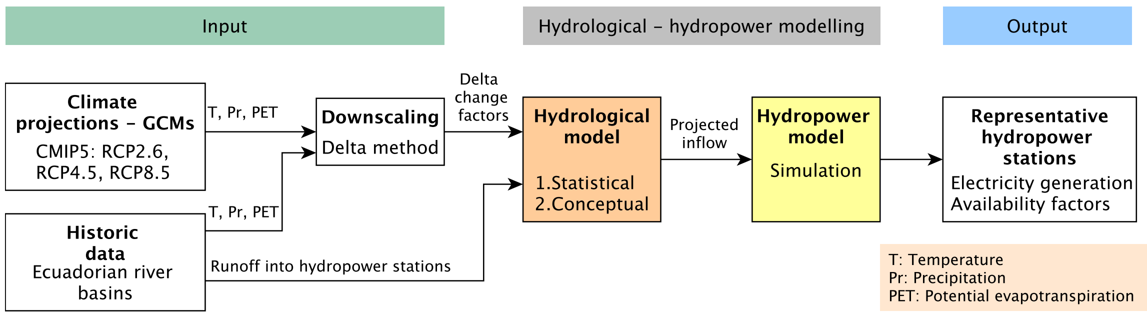
This chapter describes the methods and assumptions that are used to answer the research questions stated in this PhD. In Section 3.1, the method starts with the details of climate change projections and the models used (hydrological and hydropower) to quantify the impact of climate change on long-term hydropower generation in Ecuador. In Section 3.2, details are provided for developing an energy system optimisation model for Ecuador (TIMES-EC), including major assumptions in terms of model structure, system boundaries, and level of aggregation. Finally, the methods that have been used to assess recurring uncertainties in the energy system model (portfolio theory) are presented in Section 3.3.

3.1 MODELLING THE IMPACT OF CLIMATE CHANGE ON HYDROPOWER

The objective of this section is to show how to assess the impacts of climate change on hydrological patterns and thereof on hydropower generation. For this purpose, a hydrological model was developed and calibrated for hydropower producing rivers in Ecuador. The model was used to project inflow and assess climate induced changes by forcing it with bias-corrected outputs from a large ensemble of 40 GCMs from the CMIP5 for the period 2071–2100 run under the RCP2.6, RCP4.5 and RCP8.6 concentration scenarios (van Vuuren et al., 2011). The simulated inflow values were later used to simulate changes in the electricity output and availability factors[1] of representative hydropower stations with a hydropower simulation model. An overview of the method can be seen in Figure 3.1 on the following page.

1 The availability factor of a power plant is the ratio of its actual output over a period of time, to its potential output if it were possible for it to operate at full nameplate capacity continuously over the same period of time (according to the MARKAL/TIMES definition i.e. at the time-slice resolution level). Not to be confused with the traditional capacity factor definition, real energy a power plant produces over the theoretical energy production if the technology would operate at full nominal capacity during a year. The difference between availability and capacity factor is the time component.

Figure 3.1: Overview of climate change and hydrological assessment method



There are a number of novelties in this subsection worth noting. Firstly, this study employs a large ensemble of GCMs to cover a wide range of future climate conditions. Secondly, the study uses a simple statistical-conceptual approach that is not data intensive which can be replicated in data scarce regions. Finally, this works addresses the gap relating to the systematic investigation of uncertainty of impacts of climate change on the Tropical Andes, which has not been systematically investigated, despite the importance for hydropower deployment for the region (Finer and Jenkins, 2012b; Anderson et al., 2018).

3.1.1 *Hydrological model (Precipitation to runoff)*

The approach used to assess climate change impacts on hydrology can vary according to the scale and scope of the analysis. The size and number of river basins investigated, as well as the availability of data for measured (physical models) or calibration parameters (conceptual/statistical models), greatly influence the hydrological modelling tool to be used. The final object of the study and/or the level of detail of the results – either for the understanding of different processes within the local hydrological cycle or just for projections of a specific aspect for subsequent modelling exercises – also influence the selection of the method, as discussed in Section 3.1 on the previous page.

The method presented here is intended to be applied to various Ecuadorian river basins with the objective of generating simulated monthly inflow into existing and future[2] representative hydropower plants. Although the considered river basins are hydraulically independent from each other, the hydropower stations installed within them are interconnected through the electricity transmission network. Therefore, energy system analysis must be assessed integrally and precipitation to runoff modelling must include all hydropower electricity producing-river basins. In addition, given seasonal

2 According to the National Electricity Master Plan 2016-2025 (MEER, 2017a)

complementarity characteristics between basins and watersheds, a seasonal monthly analysis is necessary.

A statistical-conceptual hydrological model consisting of a two-step approach was selected to model climate change precipitation projections to runoff (De Lucena et al., 2009; Grijsen, 2014). The argument for this type of model over more complex physical models is that application of these latter can be challenging since their inputs can be difficult to acquire in developing countries especially in the spatially continuous manner, thus hindering the calibration and validation process (Babur et al., 2016). Inter-comparison between catchment basins is also made possible with conceptual models since historical precipitation and runoff values of main rivers are more likely to exist for a larger number of basins.

The first step consists of a statistical approach that uses 30 years of observed monthly time series of precipitation and inflow to assess the 'coefficient of hydrologic sensitivity' between precipitation and runoff into existing hydropower stations. This coefficient indicates the variation in inflow as a proportion of the variation in climatic variables. In this coefficient are implicit aspects of the hydrological cycle, such as evapotranspiration and percolation, although it is not possible to distinguish them. This limitation of statistical models may be relevant for detailed hydrological analysis. However, in the context of assessment of climatic impacts, this methodology can be very useful due to its simplicity and wide applicability, assuming that the model is well adjusted. The coefficient of hydrological sensitivity with respect to changes in precipitation can be estimated using a logarithmic linear regression model (Jones et al., 2006; De Lucena et al., 2010a), according to Equation 3.1 below:

$$ln\left(Q_t\right) = \alpha + \beta_1 ln\left(Pr_{t-m}\right) + \beta_2 d_2 ln\left(Pr_{t-m}\right) + \varepsilon_t \tag{3.1}$$

where, Q_t and Pr_{t-m} are the average observed monthly inflow and precipitation (1971–2000) for month t and a representative hydropower power station in a selected river basin.[3] Parameters α, β_1, β_2 are the estimated regression coefficients, d_2 is a categorical dummy variable,[4] and ε_t is the error term. The relevant regression coefficients are β_1 and β_2, which represent the sensitivity or 'elasticity' of average monthly inflow with respect to average precipitation.[5] The use of the logarithmic regression guarantees

3 Notice that there is a lag time m between precipitation and runoff, which has been adjusted to obtain the best model fit.

4 A categorical variable was inserted to improve regression fit and represent seasonal patterns, being $d_2 = 0$ for the dry season (from October to February) and $d_2 = 1$ for the wet season.

5 Precipitation has been identified as the leading driver for inflow in Ecuador (Célleri, 2007). In regions with little or no snow, e.g. in the Amazon, changes in runoff are much more dependent on changes in rainfall than on changes in temperature (Bates et al., 2008).

that the estimated regression coefficients represent the hydrological sensitivity with respect to the variable in question (similarly to the coefficients of elasticity of economic theory). Thus, the final coefficient of hydrological sensitivity of precipitation to inflow for each basin is according to Equation 3.2 :

$$E_{Q-Pr} = \beta_1 + \beta_2 \tag{3.2}$$

where, E_{Q-Pr} is the coefficient of hydrological sensitivity, which is equal to $\beta_1 + \beta_2$, when a month is in the d_2 period, otherwise the coefficient is equal to β_1.

Often in hydrological processes, one month's rainfall has effects on the flow of the next month due to percolation and the storage capacity of water in the soil. While physical and conceptual models attempt to address this issue by modelling the processes that result in this lagged effect, in statistical models such an effect can be estimated by the inclusion of lagged precipitation values $\left(Pr^i_{t-m}\right)$. Therefore, it is important to conduct a preliminary analysis of the data before estimating the regression equation to assess whether this occurs.

Once the coefficient of hydrological sensitivity is estimated, Equation 3.1 can be used to project inflow for any given month in a representative hydropower station, according to the Equation below:

$$Q_t^{future,GCM} = Q_t^{baseline} \times \left\{ \left[1 + E_{Q-Pr} \times \left(\Delta Pr_t^{future-baseline,GCM} - 1 \right) \right] \times \phi_{WB,t} \right\} \tag{3.3}$$

where, $Q_t^{future,GCM}$ is the projected inflow for month t for a specific GCM for the future period (e.g. 2071–2100); $Q_t^{baseline}$ is the observed average inflow for the historic period (e.g. 1971–2000); E_{Q-Pr} is the coefficient of hydrological sensitivity; $\Delta Pr_t^{future-baseline,GCM}$ is the monthly precipitation delta factor for a projected future GCM and baseline periods, and $\phi_{WB,t}$ is the water balance correction factor for a specific month (explained below).

The second step includes the conceptual equation of the water balance for a given catchment area, and can be applied to monthly, annual or climatological means, depending on the availability of data. In the first step, seasonal patterns are captured statistically but evapotranspiration[6] and storage effects are omitted (see Equation 3.3), so the second step is included to correct for total annual discharge ($\phi_{WB,t}$). The water balance equation is a mathematical relationship based on the physical principle of mass

6 Combination of evaporation from bare soils and transpiration from plants (Yates and Strzepek, 1994).

conservation (Yates and Strzepek, 1994), which for a given catchment area or river basin can be described as shown in the following equation:

$$WB = Pr - PET + \Delta S \tag{3.4}$$

where, WB is the water balance, Pr is precipitation, PET is potential evapotranspiration[7] and ΔS is storage variation in soil and underground aquifers.

Based on Equation 3.4, it is possible to make an accounting balance of the amount of water in a given river basin. Thus, based on measurements or estimates of all but one, hydrological variables, the water balance equation can be used to calculate the unknown variable by difference. Thus, the flow rate WB can be obtained based on Pr, PET and ΔS. While Pr and PET is a direct output from GCMs, storage variation ΔS needs to be estimated for other hydrological variables such as vegetations cover, type of soil, etc. However, throughout the seasonal cycle, ΔS can be negligible since the dry period presents negative values and the wet period presents positive values of similar magnitude (Arnold et al., 1998). In this sense, assuming that the total stock of water in the soil is small compared to the flow of a whole year, it is possible to reduce the annual water balance equation to only three variables. This allows to arrive at an approximation of the annual flow based on the water balance WB, defined as the difference between precipitation Pr and and potential evapotranspiration PET. The water balance is applied therefore as a monthly correction factor ($\phi_{WB,t}$) to account for other hydrological variables and is estimated with Equation 3.5:

$$\phi_{WB,t} = \frac{WB_a^{future,GCM}}{Q_a^{future,GCM}} = \frac{\sum_1^{12}\left(Pr_t^{future,GCM} - PET_t^{future,GCM}\right)}{\sum_1^{12} Q_t^{future,GCM}} \tag{3.5}$$

where, $\phi_{WB,t}$ is the water balance correction factor defined by the ratio of the future annual water balance $WB_a^{future,GCM}$ and the projected annual inflow $Q_a^{future,GCM}$. Annual water balance $WB_a^{future,GCM}$ is equal to the summation $\left(\sum_1^{12}\right)$ of monthly difference between projected precipitation $Pr_t^{future,GCM}$ and projected potential evapotranspiration $PET_t^{future,GCM}$. Projected annual inflow $Q_a^{future,GCM}$ is equal to the summation of monthly inflow estimated with Equation 3.3 before applying the water balance correction factor. PET is downscaled, analogously to Pr with Equation 3.12 on page 105.

While in the first step of the proposed hydrological modelling some elements are based on a "black box" approach that is not based directly on the concepts of physics; in the second a simplified conceptualisation of the hydrological water balance cycle is

7 The idealised quantity of water evaporated per - unit area, per unit time from an idealised, extensive free water surface under existing atmospheric conditions (Yates and Strzepek, 1994).

used. It should be borne in mind that the proposed hydrological modelling serves the purpose of providing an annual inflow time series for energy simulation. This series should incorporate possible effects of climate change on both the annual trend and the seasonal variability. The first one indicates the direction of the climate impacts in terms of increasing or reducing water availability for hydroelectric generation in the *inter-annual* level. The second has influence on the operation in the *intra-annual* level.

Hydrological model performance will be validated with a ratings approach similar to that adopted by Ho et al. (2015), with three statistical measures: i) Pearson's correlation coefficient (r), ii) Nash-Sutcliffe Efficiency (NSE) coefficient, and iii) percentage deviation (Dv) of simulated mean flow from observed mean flow.

The Pearson's correlation coefficient (Equation 3.6) determines the degree of linear relationship between the simulated and observed discharge. This coefficient ranges from 0 to 1, with higher values indicating less error variance, and, typically, values greater than 0.5 are considered acceptable. The NSE coefficient (Equation 3.7) determines how well the model is able to simulate the variation in discharge by comparing the magnitude of the residual variance with the measured data variance. NSE ranges from 0 to 1, with higher values indicating less error, and, typically, values greater than 0.5 are considered acceptable. The percentage deviation (Equation 3.8) measures the average tendency of the simulated data to be larger or smaller than their observed counterparts, in other words, it characterises the percent mean deviation between observed and simulated flows. Dv can be positive or negative, positive means underestimation and negative means overestimation, typically, values of $-15\% < Dv < +15\%$ are considered acceptable (Srinivasan et al., 2010).

$$r = \frac{\sum_{i=1}^{n}\left(X_i - X_{avg}\right)\left(Y_i - Y_{avg}\right)}{\sqrt{\sum_{i=1}^{n}\left(X_i - X_{avg}\right)^2}\sqrt{\sum_{i=1}^{n}\left(Y_i - Y_{avg}\right)^2}} \tag{3.6}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}\left(X_i - Y_i\right)^2}{\sum_{i=1}^{n}\left(X_i - X_{avg}\right)^2} \tag{3.7}$$

$$Dv = 100 \times \left(1 - \frac{Y_i}{X_i}\right) \tag{3.8}$$

where in Equations 3.6, 3.7 and 3.8, X_i is the measured value, X_{avg} is the average measured value, Y_i is the simulated value, and Y_{avg} is the average simulated value.

Finally, although an analysis with geographic detail provides better results by incorporating specificities of different segments of the catchment area of a river basin, its applicability is limited by the availability of data and computational capacity. Due to the unavailability of a broad and continuous meteorological database and due to the fact that the analysis of the Ecuadorian hydroelectric sector cannot be done in a disaggregated way, the aggregation of climatic effects in hydrographic basins becomes a simplifying and necessary premise.

3.1.2 *Hydropower model (Runoff to hydropower generation)*

In order to assess the impacts of climate change on hydropower generation, a reference scenario must be constructed. Simulated hydropower generation based on altered inflow time-series are subsequently compared to the reference scenario, as to find relative impacts. Due to the enormous uncertainty inherent in climate projections, it is prudent to work with rates of change, trends and directions, applying them to the values obtained through simulations with historical data. The simulated hydropower generation with historical hydrological time-series corresponds, in principle, to the historical operation of the hydropower system and, for the purposes of energy planning, this is the reference normally used. In the context of calculating impacts, what is important is the variation between climatic scenarios and the historical operation scenario. The impact of climate change should therefore be analysed in the form of rates of change, where the proposed measure of impacts is the variation in the availability factor of hydroelectric plants.

To assess the behaviour of the hydropower dam operators to runoff availability, a hydropower simulation model is used. Analysis of hydropower electricity generation output is developed purely under a water availability perspective, disregarding possible benefits of thermal complementation or uncertainties about the electric energy market that can affect the operation of hydropower systems. The hydropower model simulates monthly available water that can be released for hydropower generation using reservoir specifications and according to the inflow time series generated by the previously detailed hydrological model. Releases are specified for each month of the year, as well as reservoir level and spillage. Storage dynamics are simulated using the laws of mass balance according to Equation 3.9 as follows:

$$\begin{aligned} S_t = & S_{t-1} + Q_t + V_t^* - V_t \\ & 0 \leq S_t \leq S_{usable} \\ & V_{min} \leq V_t \leq V_{max} \end{aligned} \tag{3.9}$$

where, S_t in the reservoir storage in month t, Q_t is the current period reservoir inflow, V_t^* is the water release or spillage from an upstream hydropower dam (if any) and V_t

is the water release volume to the turbines. S_{usable} is the maximum usable storage of the reservoir, V_{max} is the maximum volume of water that can be released through the turbines for the hydropower station to work at maximum capacity in each period, and V_{min} is the minimum release that must satisfy turbine operation, downstream hydropower stations requirements and environmental flows. Notice that, evaporation from the reservoir has been omitted. Recent studies by Bakken et al. (2016) have found that water consumption rates of hydropower stations are very close to zero (i.e. evaporation from the host environment before and after creation of the hydropower plant are the same) in humid and wet environments such as in the Tropical Andes. This could of course change with increasing temperatures and climate change, and depending on the the free surface area of the reservoir. This must be assessed in further research. In this thesis, evaporation has only been captured at the basin level as was mentioned previously for the hydrological model.

Monthly hydropower electricity generation E_t (in MWh) and availability factor AF_t is simulated with Equation 3.10 and Equation 3.11, respectively, as follows:

$$E_t = \eta \cdot \rho \cdot g \cdot H \cdot V_t \tag{3.10}$$

$$AF_t = \frac{E_t}{(P \cdot T)} \tag{3.11}$$

where, η is plant efficiency, ρ is the water density, g is gravitational acceleration, H is hydraulic head and V_t is the inflow into the turbine. Efficiency η accounts for turbine efficiency and friction losses, and is used as a calibration parameter. Hydraulic head considers penstock vertical head plus average dam height. In the availability factor Equation, P is nominal capacity (in MW) of the hydropower station and T is number of hours in a month. The availability factor is chosen since hydroclimatic conditions are generally integrated into energy system models by exogenously defining this parameter of hydropower power generation technologies to characterise their seasonal operation (Gargiulo, 2009; Kannan and Turton, 2011; Lind and Rosenberg, 2013).

A final advantage of the detailed model is that it allows the assessment of the impact that the availability of inflow has on individual or aggregated hydropower plants in a system. To calibrate and validate the model, simulated hydropower production will be compared to historical production selected hydropower stations that represent different types of hydropower facilities i.e. single/cascading and run-of-river/reservoir. Hydropower electricity model performance will be validated similar to Yi Ng et al. (2017), with two statistical measures: Pearson's correlation coefficient (r) and the standard error (ε) .

3.1.3 *Study area and data*

3.1.3.1 *Study area*

Ecuador is located in the northwest part of South America in the region known as the Tropical Andes (see Figure 3.2 on the next page). The Andes define the hydrographical system of the country and its river basins: the Pacific region that discharges into the Pacific Ocean and the Amazon region which consists of main tributaries to the Amazon river. Overall, spatial precipitation patterns are highly variable, with annual precipitation ranging from over 3,000 mm in the Amazonian slopes to less than 500 mm in the southwest part of the country (Buytaert et al., 2011), while seasonal variability ranges from 350 mm/month in the rainy season to lower than 100 mm/month in the dry season (Espinoza Villar et al., 2009).[8]

In this study, six large river basins that are relevant for hydropower generation are represented with a total area of around 166,000 km^2 (see Table 3.1 on page 104). Three of these basins belong to the Pacific region: Esmeraldas, Guayas and Jubones, while three belong to the Amazon region: Santiago, Agoyan and Napo (see Figure 3.2 on the next page). Given the scarcity of measured historical precipitation and temperature datasets, the effects of climatic variations (rain and temperature) need to be aggregated by river basin, as defined by the hydrographic regions of the Ecuadorian National Secretariat of Water (SENAGUA, 2009). Thus, for all hydropower plants belonging to the same basin, the estimated impacts are the same regardless of their position within the basin. The precision gain of an analysis made from the catchment areas of each plant individually would be small in view of the fact that some plants have a very small catchment area and the climate projections are not so precise. In addition, when aggregating by basin, it is avoided that possible outliers of the climatic projection interfere significantly in the flow results. Finally, in view of the large computational effort required for the individual analysis of over 35 existing hydropower plants in Ecuador corroborates the level of aggregation used.

3.1.3.2 *Observed Data*

Observed historic mean monthly inflow into hydropower stations for a 30-year period (1971-2000) were provided by the National Electricity Grid Operator (CENACE). Due to the lack of historic datasets of inflow that cover larger areas of the catchment, the

8 Even though small glaciers are present in the Ecuadorian Andes, strong solar radiation precludes the development of a seasonal snow cover. Snowmelt therefore does not provide an additional, seasonally-changing water reservoir, meaning that precipitation and evapotranspiration remain the leading hydroclimatic drivers (Kaser et al., 2003, 2010; Vergara et al., 2007).

Figure 3.2: Ecuador's six major river basins, hydropower stations and gauging stations used in this study

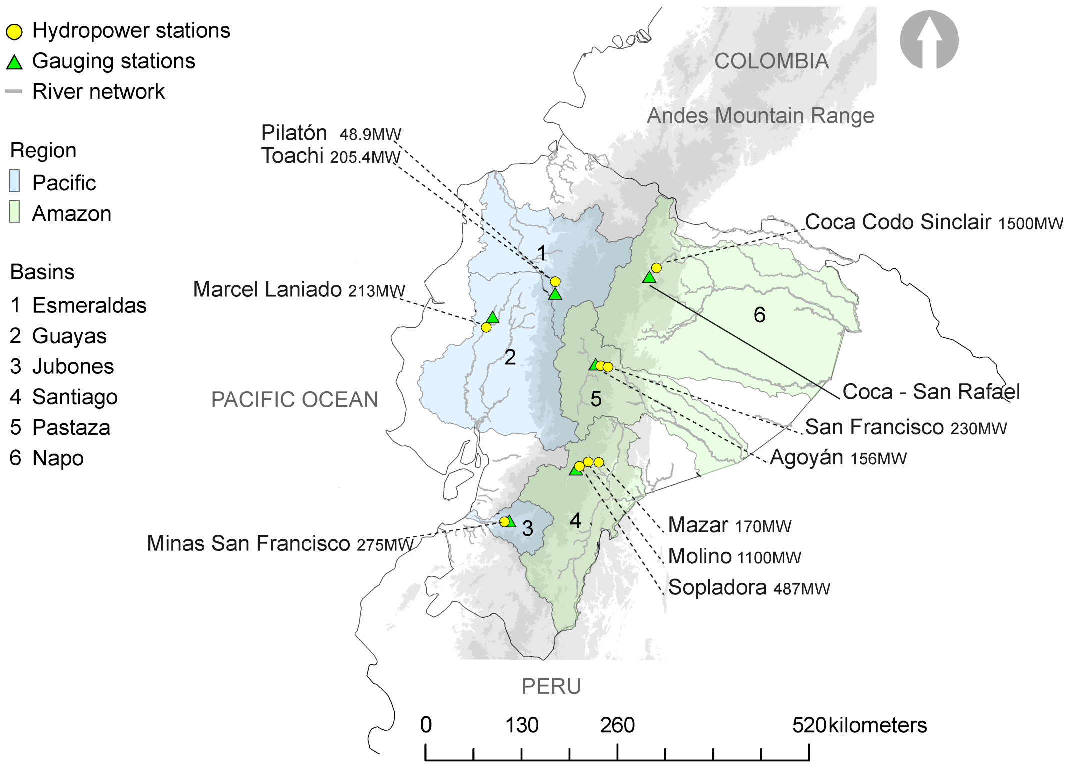
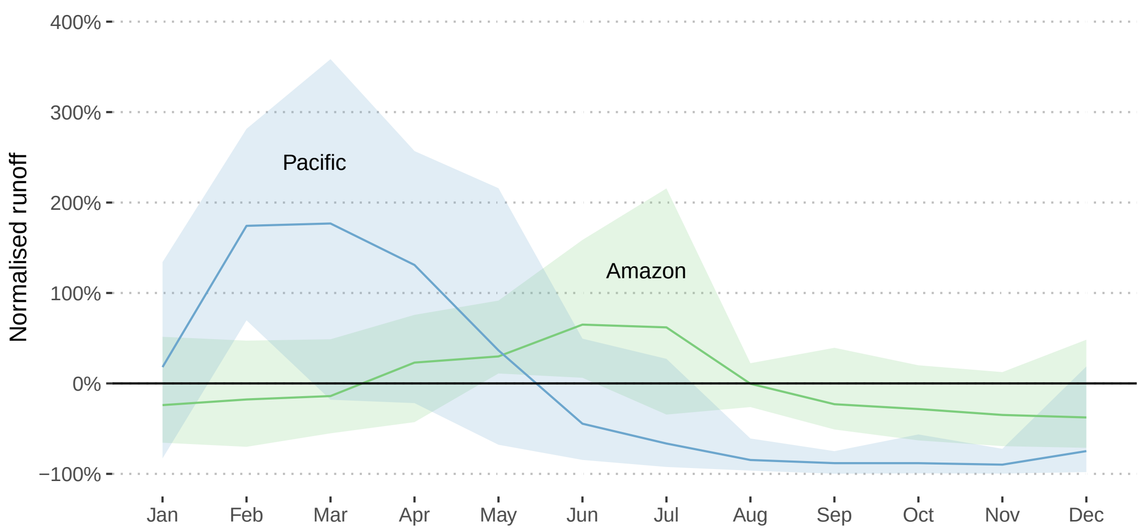
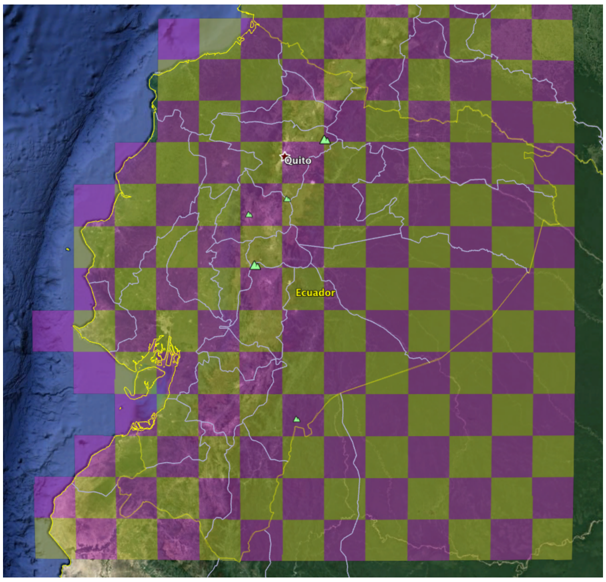


Figure 3.3: Average normalised runoff in the Amazon and Pacific regions (1971-2000)



Note: The shaded areas show the range of maximum and minimum runoff registered values.

Figure 3.4: Grid cells for historic meteorological data at a 0.5° × 0.5° resolution for Ecuador available from the Climate Research Unit of the University of East Anglia

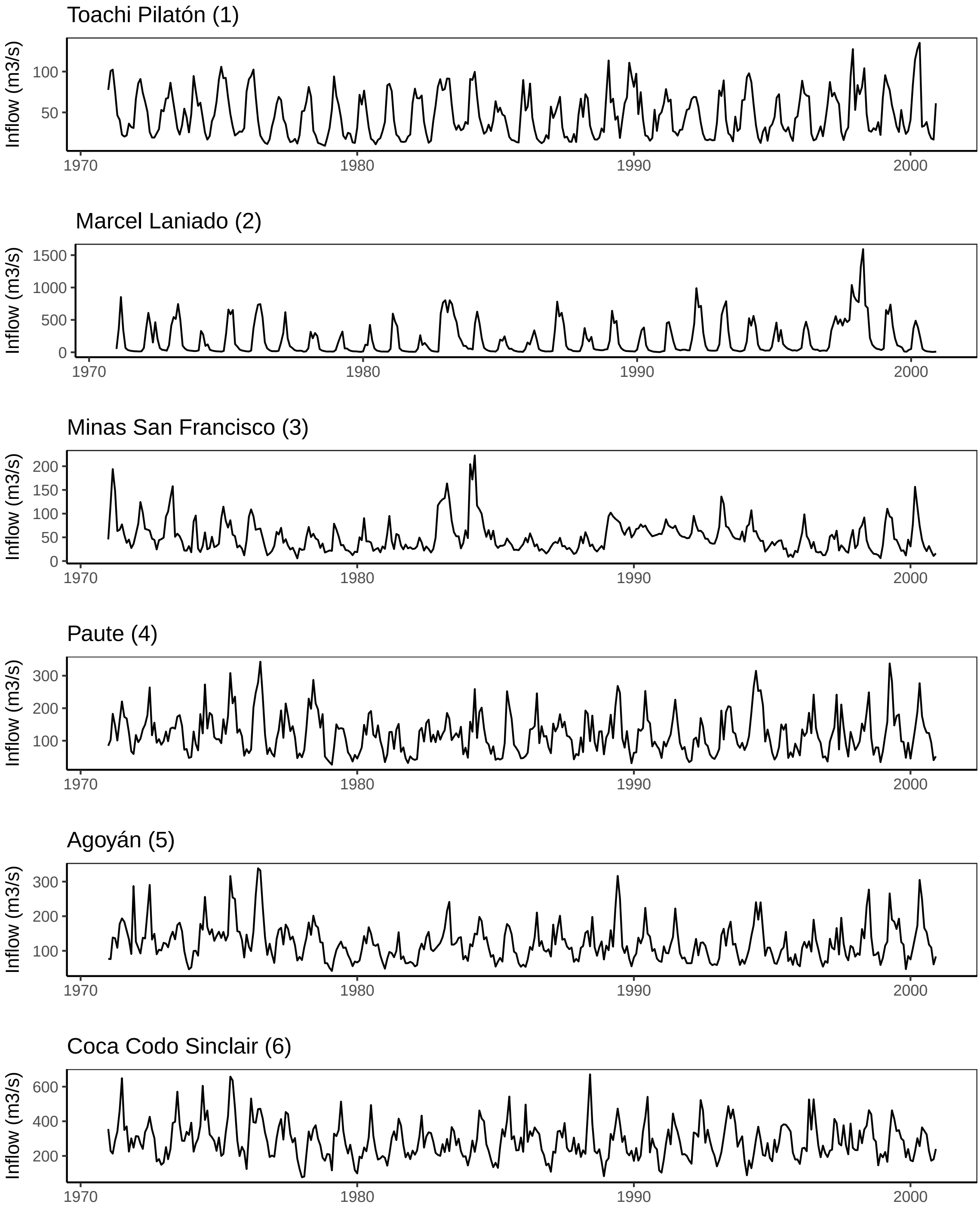


analysis needs to be done for a limited number of inflow gauging stations that have to be used to characterise the catchment basin. Figure 3.2 on the facing page shows the location of gauging stations for which runoff data is sufficient for estimation and that can be used as reference for the hydropower plants which they belong to. However, to assure their validity, we compared these unregulated inflow values with quality-assured data from the Global Runoff Data Centre (GRDC, 2016) and corroborated that the values provided by CENACE were consistent with data that has passed quality control procedures and plausibility checks. The characterisictic normalised inter-annual inflow pattern of each of the regins can be seen in Figure 3.3 on the preceding page, showing certaint complementarity during the first half of the year, but coincident low flows towards the end of the year. The shaded areas show the range of maximum and minimum inflow registered values between 1971-2000). Figure 3.5 on the following page presents the obtained inflow 30-year time series for the six rivers that are assessed.

Observed historic mean monthly temperature, precipitation and potential evapotranspiration (PET) for Ecuador for a 30-year period (1971–2000) were extracted from the dataset of the University of East Anglia Climate Research Unit (CRU) TS v.3.24 (Harris et al., 2014), release of October 2016. The gridded data set has a resolution of 0.5° × 0.5°, and the studied river basins lie within 65 grid cells (see Figure 3.4).

In this study, the mean observed values of meteorological data for each month of the year are compared with the respective mean observed values of inflow into hydropower stations. Thus, the proposed method attempts to circumvent the limitation related to the availability of daily precipitation data through the use of monthly averages in a panel data analysis for reference plants in each basin. If, on the one hand, the temporal

Figure 3.5: Time series of inflow into representative hydropower stations in Ecuador (1971 - 2000)



dimension reduces to 12 observations (one per month), on the other hand there is an increase in spatial dimension, given by the number of stations and hydropower plants considered all over the country. This procedure also tends to improve the correlation between the rainfall and flow series by levelling the outliers, i.e. out of trend events.

The hydropower simulation model will be applied to six hydropower systems in which Ecuador's ten largest hydropower stations operate, their technical details are depicted in Table 3.1 on the following page. The installed capacity of these systems total 4,368 MW which is over 95% of Ecuador's current hydropower capacity (see Table 3.6 on page 114) Technical characteristics of these facilities including head, usable storage, design flow rate, efficiency and observed mean monthly flow (1971–2000) and electricity production were provided by CENACE (CENACE, 2015).

Table 3.1: Technical characteristics of hydropower stations used in this study

Basin	Area (km^2)	River	Hydropower system	Hydropower station	Capacity (MW)	Generation (GWh/y)	Capacity factor	Storage (Hm^3)***	Head (m)	Design flow (m^3/s)	Location (°)	
											Lat.	Lon.
Pacific region												
1. Esmeraldas	21,553	Pilaton	Toachi Pilaton	Pilaton*	48.9	224	0.52	-	149	28.6	-0.31	-78.96
				→Toachi*	205.4	896	0.50	2	235	100	-0.31	-78.97
2. Guayas	32,218	Daule	Marcel Laniado	Marcel Laniado	213	717	0.38	4,069	55	397.5	-0.92	-79.37
3. Jubones	4,361	Jubones	Minas S. Francisco	Minas S. Francisco*	275	1,290	0.54	6	474	65	-3.31	-79.52
Amazon region												
4. Santiago	24,920	Paute	Paute Integral	Mazar	170	900	0.60	302	159	141.1	-2.59	-78.62
				→Molino	1,100	4,800	0.50	44	660	220	-2.59	-78.56
				→Sopladora**	487	2,800	0.65	-	363	150	-2.57	-78.47
5. Pastaza	23,190	Pastaza	Agoyan	Agoyan	156	1,080	0.79	0.8	150	120	-1.39	-78.38
				→San Francisco	230	1,400	0.70	-	213	116	-1.39	.78.35
6. Napo	59,505	Coca	Coca Codo Sinclair	Coca Codo Sinclair**	1,500	8,734	0.66	-	620	287	-0.12	-77.44
Total	165,747		Total		4,368	22,841	0.59					

Notes: *Under construction in 2018, **Started operation in 2016, ***Usable storage. Cascading systems are shown with arrows (refer to Figure 3.2).
Source: CENACE (2015); MEER (2015); MICSE (2016b)

3.1.3.3 *Future climate data*

The future climate data under RCPs were downloaded from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer database (Trouet and Van Oldenborgh, 2013). Forty GCMs under RCP2.6, RC4.5 and RCP8.5 from CMIP5 were considered for this study. These GCMs cover diverse resolutions, varying from 0.94° × 1.25° to 2.8° × 2.8°, come from different climate centres all around the world and are updated beyond the year 2000 (van Vuuren et al., 2011). The data for these GCMs, for selected RCPs, were downloaded for precipitation and potential evapotranspiration. The forcing intensities of these three RCPs are 2.6 W/m² 4.5 W/m² and 8.5 W/m², respectively, and approximately conform to the low, medium and high condition of climate change impact (see Section 2.2.1 on page 35). The GCMs used for climate projection in the study area are presented in Table 3.3 on page 107. These GCMs cover the period from 1971 to 2100, which is divided into two 30-year periods: baseline period (1971–2000) and one future time horizon (2080s: 2071–2100).

GCMs were not selected based on vintage, resolution, validity and representativeness of results. The combination of GCMs can be used even though they may not necessarily be the best models for the area, however the intention of this study is to map the full range on uncertainty surrounding GCMs (Krysanova et al., 2018). Monthly precipitation and PET data for each GCM were obtained for the six basins using a bilinear interpolation approach, against which baseline period values were compared by linear scaling (LS), i.e. the delta factor approach (Fowler et al., 2007). Linear scaling aims to perfectly match the monthly average of corrected values with observed ones (Hu et al., 2013; Fang et al., 2015). The monthly corrected values are constructed upon the differences between observed and raw GCMs data. Data was bias-corrected using precipitation and PET values from the historic observed baseline period CRU datasets (Babur et al., 2016). Monthly differences of the climate data, are obtained using observed period (1971–2000) of raw GCMs and observed data. Equation 3.12 is applied to bias-correct GCMs future precipitation data (Babur et al., 2016):

$$Pr_t^{future} = Pr_t^{future,GCM} \times \left(\frac{Pr_t^{historic,observed}}{Pr_t^{historic,GCM}} \right) \tag{3.12}$$

The linear scaling method's limitations are related to the strong assumptions it makes about the nature of the changes, including a lack of change in the variability and spatial patters of climate, and that some extreme values are overlooked when working with averages (Roy et al., 2010). The lack of meteorological data and high variability of the climate system in the Tropical Andes region complicate the use of more complex downscaling methods (Buytaert et al., 2010).

Table 3.3: GCMs used in this study from the CMIP5

No.	Model	Institution
1	ACCESS1-0	Commonwealth Scientific and Industrial Research Organisation (CSIRO) and Bureau of Meteorology (BOM), Australia
2	ACCESS1-3	
3	BCC-CSM1.1	Beijing Climate Centre, China Meteorological Administration
4	BCC-CSM1.1(m)	
5	BNU-ESM	College of Global Change and Earth System Science, Beijing Normal University
6	CanESM2	Canadian Centre for Climate Modelling and Analysis
7	CCSM4	National Centre for Atmospheric Research
8	CESM1-BGC	Community Earth System Model Contributors
9	CESM1-CAM5	
10	CMCC-CM	Centro Euro-Mediterraneo per I Cambiamenti Climatici
11	CNRM-CM5	Centre National de Recherches Meteorologiques
12	CSIRO-Mk3-6-0	Commonwealth Scientific and Industrial Research Organisation (CSIRO)
13	EC-EARTH	EC-Earth Consortium
14	FGOALS-g2	LASG, Institute of Atmospheric Physics, Chinese Academy of Sciences
15	FIO-ESM	The First Institute of Oceanography, SOA, China
16	GFDL-CM3	NASA Goddard Institute for Space Studies
17	GFDL-ESM2G	
18	GFDL-ESM2M	
19	GISS-E2-H p1	
20	GISS-E2-H p2	
21	GISS-E2-H p3	
21	GISS-E2-H CC	
23	GISS-E2-R p1	
24	GISS-E2-R p2	
25	GISS-E2-R p3	
26	GISS-E2-R CC	
27	HadGEM2-CC	Met Office Hadley Centre
28	HadGEM2-ES	
29	INM-CM4	Institute for Numerical Mathematics
30	IPSL-CM5A-LR	Institute Pierre-Simon Laplace
31	IPSL-CM5A-MR	
32	IPSL-CM5B-LR	
33	MIROC5	Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute of Environmental Studies, and Japan Agency for Marine-Earth Science and Technology
34	MIROC-ESM	Japan Agency for Marine-Earth Science and Technology
35	MIROC-ESM-CHEM	Ocean Research Institute and National Institute of Environmental Studies
36	MPI-ESM-LR	Max-Planck-Institute für Meteorologie
37	MPI-ESM-MR	
38	MRI-CGCM3	Meteorological Research Institute
39	NorESM1-M	Norwegian Climate Centre
40	NorESM1-ME	

3.1.4 *Climate change scenarios*

The hydropower simulation model was run for six large representative hydropower systems in Ecuador (see Table 3.1 on page 104.) and for four scenarios of seasonal inflow patterns: i) historical or no climate change, ii) mean of the CMIP5 ensemble RCP4.5 scenario, iii) +1 standard deviation of the CMIP5 ensemble RCP4.5 scenario, and iv) -1 standard deviation of the CMIP5 ensemble RCP4.5 scenario (see Figure 4.6 on page 190). Table 3.4 shows these four scenarios that have been defined to represent the diverse range of possible runoff projections for Ecuador. The simulated operation from the historical hydrological series (i) is a proxy of the historical (30-years average from 1971 to 2000) operation that considers no climate change and, for the purposes of energy planning, this is the reference used. The Mean scenario (ii) was done in such a way as to maintain the methodological consistency of other studies which use the ensemble mean of a concentration scenario for the analysis (Ho et al., 2015). The standard deviation (iii and iv) is used to inform the minimum and maximum limits explored in this study, following its widespread application as a common measure of uncertainty in risk analysis approaches and investment portfolio analysis for the power sector (Awerbuch and Yang, 2007). The ±1 standard deviation is used in this study to parameterise the probability space of the CMIP5 ensemble under RCP4.5 for the period 2071–2100 and will be used as the hypothetical Wet and Dry scenarios cases. The Wet and Dry scenarios imply the strongest impacts of climate change on water resource availability.

It must be mentioned that, the framework applied in this thesis was also applied for the RCP2.6 and RCP8.5 scenarios, however differences among RCPs (intra-model) were found to be smaller compared to inter-GCM (inter-model) differences. Inter-GCM uncertainty range was also found to have similar magnitude for all three concentration scenarios. Another reason to use only one concentration scenario, is that the RCP4.5 is

Table 3.4: Long-term climate change scenarios for Ecuador

Climate change scenarios	Description
NoCC	30-year average of historic values, representing constant hydroclimatic variables
Mean	mean of the CMIP5 ensemble of individual GCMs for RCP4.5
Wet	+1 standard deviation of the CMIP5 ensemble of individual GCMs for RCP4.5
Dry	-1 standard deviation of the CMIP5 ensemble of individual GCMs for RCP4.5

the scenario that gathers more GCM models. RCP4.5 contains results from 41 GCMs compared to 26 GCMs for the RCP2.6, 17 GCMs for RCP6.0 and 30 GCMs for RCP8.5 (van Oldenborgh et al., 2013). Considering that the discrepancy of GCM models is to be assessed, the GCM scenario that has the most modelling results is chosen, i.e. RCP4.5. A final reason to use the RCP4.5 is that it is considered to represent a central estimate of future climate impacts (Thomson et al., 2011) and also most closely aligns with the core objectives of the United Nations 2015 Paris Agreement (UNFCCC, 2015a), which include limiting anthropogenic warming to no more than 2°C above pre-industrial values by 2100 (IPCC, 2013).

Because the range of uncertainty for precipitation and inflow values were found to be so broad (see Figure 4.2 on page 186 and Figure 4.6 on page 190), using the extremes would challenge the subsequent modelling activities (and the interpretation of results). For example, working with GCM that presented the highest projection for inflow (see maximum values in Table 4.2 on page 189), would have led to a power sector dominated entirely by hydropower, in which this technology would have had close to 100% availability and displaced all other technology options. Conversely, using the GCM with the lowers projection for inflow, would have meant a situation in which rivers almost completely dry up and the model would have consequently eliminated hydropower as an available expansion option.

While these extremes are plausible, given that all the projections from GCMs in the CMIP5 are considered to be equiprobable (Ho et al., 2015), they would not have allowed the assessment of the energy system's sensitivity to changes in water availability. Therefore the standard deviation granted a possibility to construct and explore intermediate long-term climate occurrences that are within the uncertainty space of the GCM ensemble of projections. Therefore, this thesis could be considered to work with a *hybrid* approach towards climate scenarios, between climate change impact studies on hydropower that define merely hypothetical scenarios (e.g. Madani and Lund, 2010; Dale et al., 2015) and studies that rely exclusively on GCM outputs (e.g. Teotonio et al., 2017; Seljom et al., 2011).

Not using the extreme cases of the projections has implications on the interpretation of the results. First, that the extreme cases which are likely probable are left out, and therefore the possibility of a scenario in which hydropower resources dry out is totally underestimated. This type of scenario would recommend that the system avoid any more hydropower investments and would certainly mean that current hydropower would become stranded assets. In addition, it would advocate for rather focusing on other issues beyond hydropower, such as the water availability for agriculture and industry. On the other side of the spectrum, and extremely wet scenario, could also happen, and while theoretically would be beneficial for hydropower, too much rain would also put other infrastructure at risk, due to floods and landslides in eroded areas. The methodology here is energy-focused and leaves these broader impacts of extreme changes to other researchers. The results following the proposed methodology should be interpreted as how sensitive hydropower is to changes in its underlying assumptions of water availability and infrastructure costs. If changing of these input parameters suggests that the power matrix should still deploy hydropower, then this technology can be considered as robust, if not, it is suggested that the reliance of this technology be more conservative and other technologies should come to play.

3.2 MODELLING OF ECUADOR'S ENERGY SYSTEM – THE TIMES-EC MODEL

The energy sector interacts with all other sectors of the economy. Within the energy sector, the electricity sector is particularly relevant, both as an energy supplier and as a consumer of energy resources. The various interrelationships within the energy sector and its interactions with other sectors of the economy mean that the effect of climate change on hydroelectric generation is overarching. Impacts of climate change should therefore be evaluated comprehensively, considering not only the electricity sector, but also the broader energy sector and even other economic sectors.[9]

In this sense, the methodology proposed here for the assessment of impacts of climate change and the calculation of least-cost adaptation options for the power sector seeks to evaluate the energy sector through an integrated prism, considering all energy chains[10] and the relationships between them. The idea behind the proposed approach is to compare the optimal evolution of the energy sector when incorporating long-term scenarios of projected impacts of climate change and possible energy policy choices regarding the use of hydropower (Carvajal et al., 2019). The results obtained from the modelling are scenarios that project the optimal configuration of final energy supply including the technological portfolio for power generation.

Therefore, the main advantage of using an integrated framework for the energy sector, rather than specific models for the electric sector to calculate optimal adaptation options, is that information can be obtained regarding the second order effects on the whole system of supply and demand for energy. Thus, it is possible to evaluate to what extent the

9 The interaction with the different sectors of the economy can be assessed further with an iterative methodology with a computable general equilibrium (CGE) model or an Integrated Assessment Model (IAM).

10 Understanding all stages of energy production and consumption, i.e. primary energy production, transformation, transportation, distribution and final consumption.

optimal adaptation measures designed for the electricity sector can affect the consumption of energy in sectors such as industry, residences, etc. To achieve this, an energy system optimisation model has been selected as the appropriate modelling tool, since it combines *top-down* assumptions, such as economic and demographic growth, with *bottom-up* sectoral assumptions and constraints on the availability of energy resources and energy conversion technologies.

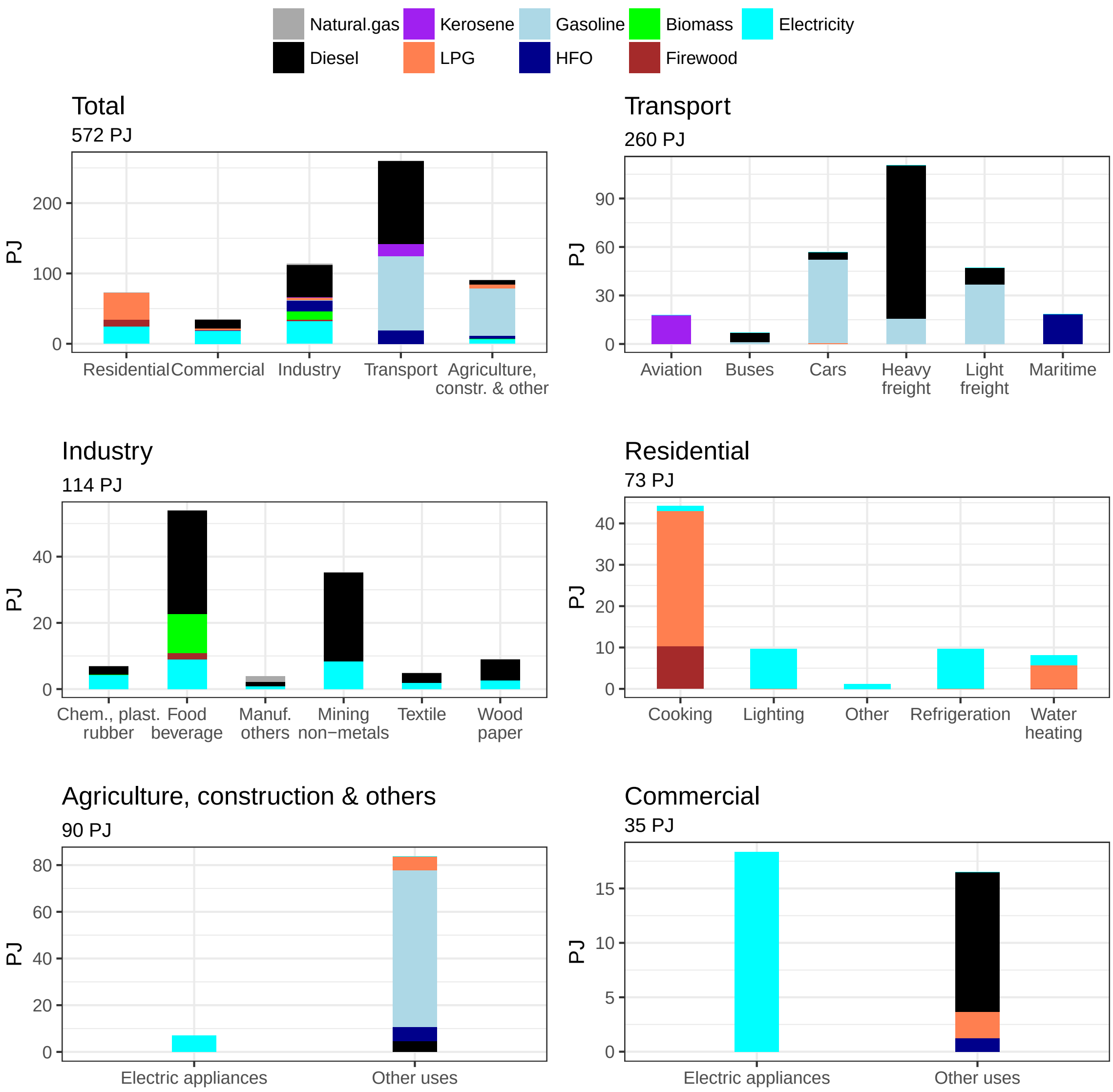
In the following subsections an overview of the Ecuadorian energy system is presented, followed by a description of the structure and assumptions used in the energy system model describing the Ecuadorian energy system (TIMES-EC). Subsequently, given the scope of this thesis, a detailed description of how hydropower has been implemented in the model is presented, together with considerations for modelling other elements of the power sector, energy resources and energy demand. Finally, the approach for scenarios and policy choices is discussed in the context of Ecuadorian energy and development policy.

3.2.1 *Overview of Ecuadorian final energy and electricity demand*

Ecuador is an upper middle-income country (ECLAC, 2017) with an overall advanced position in terms of energy access, both in relation to end-use energy demand for heat and in terms of electricity service coverage (>97%) (IRENA, 2015a; REN21, 2017). Ecuador's final energy demand reached 572 PJ in 2016 (MICSE, 2016b). Figure 3.6 on the following page presents total final energy demand by sector and fuel and energy service demand. The transport sector is the largest final energy consumer (46%), followed by industry (19%) and the residential sector (13%), with the remaining used by commerce (6%) and agriculture, construction & others (16%). Diesel, gasoline, electricity and LPG are the main fuels used in Ecuador. Diesel and gasoline are the predominant fuel sources in the transport sector. Industry and the commercial sector mostly use diesel and electricity. The residential sector is characterised for using electricity (lighting and refrigeration) and LPG (cooking and water heating) (MICSE, 2016b).

Heavy freight is the largest consumer of energy in the transport sector in 2016 (110 PJ) which is mostly powered by diesel, as can be seen in Figure 3.6 on the next page. The Ecuadorian transport fleet is powered mainly by gasoline and diesel (over 95%), with the remainder using heavy fuel oil (HFO) (maritime) and kerosene (Aviation). Regarding the industrial sector, the food & beverage and the mining & non-metals sectors account for over 80% of energy consumed in in 2016. This reflects the structure of the Ecuadorian economy, with a large agricultural sector and a producer of raw mining commodities,

Figure 3.6: Total energy demand by fuel and main consumption sectors in Ecuador in 2016



especially crude oil. In the residential sector, more than half of final energy demand is for cooking, where LPG has a predominant role. Electric lighting and refrigeration are the energy services that most consumed electricity and do so in similar shares. The commercial sector is the smallest energy consumer. Over half of its consumption is electricity, mainly for lighting.

Total electricity consumption in Ecuador was close to 23 TWh in 2017; the residential sector was the largest consumer with a share of 32%, followed by the industrial sector at 25%, the commercial sector at 17% and the remaining usage accounted for by others such as public lighting and losses. Total annual electricity demand has grown at an average rate of 5.8% per year over the last decade (2007-2016) MEER (2017a). Table 3.5 on the facing page shows a summary of electricity demand by sectors.

Table 3.5: Electricity demand in Ecuador by sectors in 2017

	Sector	Demand (GWh)	(%)
Electricity consumption in the SNI	Residential	7,288.25	32%
	Commercial	3,846.81	17%
	Industrial	5,747.52	25%
	Public lighting	1,220.55	5%
	Others	2,176.05	10%
Total consumed		20,279.18	89%
Transmission and Distribution losses	Technical	1,670.61	7%
	Non-technical	976.59	4%
Total losses		2,647.20	12%
Total dispatched		22,926.38	100%

Source: ARCONEL (2018b)

3.2.2 *Ecuadorian power generation system*

The Ecuadorian power system is, in fact, a *hydrothermal* one – thermal power plants are used to complement the generation from hydropower plants (MEER, 2017a). The power sector is vertically integrated and the State owns and operates most of the installed capacity in the country (CELEC, 2013). Total installed capacity in the Ecuadorian power system was 7,434 MW in 2017 (ARCONEL, 2018b). Hydropower installed capacity in Ecuador reached 4,486 MW, which represents 60% of the total installed capacity, with the remaining capacity being gas and fossil fuel thermoelectric plants (37%) and by other renewables (3%) (solar, wind, biomass and biogas). The share of hydropower electricity generation in the national grid reached almost 83% in 2017, while the share of fossil fuel generation was 15% and other non-hydro renewable energy sources remained roughly above 2% (ARCONEL, 2017). Hydropower capacity associated with flexible reservoir (DAM) systems is 2,162 MW while run-of-river (ROR) systems comprise 2,324 MW. A summary of the installed power generation capacity in Ecuador is shown in Table 3.6 on the next page.

Initiatives to deploy non-hydro renewable energy projects have historically been weak, as evidenced by the small capacities of PV, wind and biomass in the Ecuadorian grid. The first and only grid-tied wind park in Ecuador (16.5 MW) was commissioned in 2012 (Vizhñay, 2013). There are no further wind parks under construction at the the time of writing nor policies towards future deployment of wind power. A number of small solar PV plants (~1 MW each) which total a capacity of 25 MW have been deployed in Ecuador since 2014, due to a one-time feed-in tariff regulatory framework that was launched in 2011 (CONELEC, 2013). No further PV projects are being constructed or considered

Table 3.6: Installed capacity and electricity generation in Ecuador in 2017

Source	Capacity		Generation	
	MW	%	GWh	%
Hydropower	4,486	60.3%	20,380	82.9%
Wind	21	0.3%	67	0.3%
PV	25	0.3%	34	0.2%
Biomass	136	1.8%	423	1.7%
Biogas	6	0.1%	30	0.1%
Geothermal	-	0.0%	-	0.00%
Thermal ICE	1,551	20.8%	1,091	4.4%
Thermal OCGT	775	10.4%	1,237	5.1%
Thermal ST	431	5.8%	1,279	5.2%
Subtotal	7,434	100.0%	24,545	99.9%
Interconnection	635		18	0.01%
Total	7,434	-	24,564	100.0%

Notes: Hydropower includes reservoir systems (2,162 MW) and run-of-river (2,324 MW), PV is utility scale solar photovoltaic, wind is on-shore, biomass is with bagasse-fired steam turbines, OCGT is open cycle gas turbine, ST is steam turbine and ICE is internal combustion engine.
Source: ARCONEL (2018b)

by the government. Notice in Table 3.6 that there is an interconnection capacity of 635 MW, which has served as a way to hedge against blackouts and to export surplus electricity generation, mainly to Colombia. Good connection to neighbouring countries can also function as a flexibility measure and therefore interconnections can play a key role between countries. However, no further plans of increasing this capacity is currently in place.

A small fraction of thermal generation is produced with direct-combustion of biomass (sugarcane bagasse) in steam plants (136 MW) and the first grid-tied landfill biogas plant (6 MW) was commissioned in 2016 (ARCONEL, 2018a). Given the recent additions of hydropower, thermal generation is currently playing a reserve and back-up role in the occurrence of low inflows into hydropower stations.

In Ecuador, there is one power transmission network, the Interconnected National System (SNI),[11] which integrates different sources of generation and transmits electricity to key consumption centres in the Ecuadorian Highlands and along the Pacific coastline.[12] Since the Ecuadorian power system is based mainly on hydroelectric power plants, some

11 In the country, only 12 % of the electricity is generated outside the SNI, in small isolated systems located mainly in the Amazon region in oil production fields (ARCONEL, 2017).

12 Consumptions centres located int the Pacific region of Ecuador consume 57% of total electricity, followed by centres in the Highlands with 40%. This totals 97% of all electricity generated in Ecuador. The remaining is consumed in isolated regions in the Amazon to the east and in the Galapagos Islands (ARCONEL, 2016).

characteristics of the operation of this type of generation are worth noticing in the context of the SNI.[13]

Firstly, unlike thermal plants in which, by guaranteeing the supply of fuel, there is a greater degree of control over generation, the production of electricity in hydroelectric plants depends on water availability, which is an element of a stochastic nature and, therefore, of great uncertainty. Second, all hydroelectric plants have some capacity to store water in reservoirs. This storage capacity, however, can be equivalent to a few hours – compensating for intra-daily flow variations –, some months – compensating for seasonal variations – or even for a few years – compensating for annual hydrological variations. In Ecuador, roughly half of the installed capacity of SNI is based on plants with a reservoir with monthly storage capacities and the remaining is run-of-river with only hourly flexibility at most. This requires the operator to plan expansion and manage the system to obtain the maximum generation through the interaction of these two types of hydropower technologies (De Lucena et al., 2010a).[14]

Finally, another aspect concerns the fact that the length and flow of Ecuadorian rivers causes several hydroelectric plants to exist along the same river, as is the case of the *Paute Integral* hydropower system, in Southern Ecuador (see Figure A.1 on page 291 in Appendix A). Only in the Paute river, there are four consecutive plants (Mazar 170 MW, Molino 1,100 MW, Sopladora 520 MW and an additional planned project Cardenillo 596 MW)(CELEC, 2018a), which combined (2,386 MW) form the largest and most important power generation system in the SNI. Therefore, the strategy of operating a plant cannot fail to consider all the others downstream, as it depends on the operation of the plants that are upstream.

3.2.3 *The TIMES energy system model generator*

3.2.3.1 *TIMES methodology*

This research used the TIMES (The Integrated MARKAL-EFOM System) energy system optimisation model generator, which is a widely used bottom-up optimisation modelling platform developed as part of the International Energy Agency – Energy Technology Systems Analysis Program (IEA-ETSAP) (Loulou and Labriet, 2008; Gargiulo and Gallachóir, 2013). TIMES provides a detailed techno-economic description of resources,

13 A single line diagram of the SNI can be found in Appendix A on page 289.
14 See section 1.3.2 on page 12 for further details on these technologies.

energy carriers, conversion technologies and energy demands.[15] The model minimises the total discounted costs of deploying technologies required to cover energy service demands over a multi-decadal time horizon. It can be used to examine investment decisions and help evaluate how energy and environmental policies impact the energy sector (Endo, 2007; McCollum et al., 2012; Deane et al., 2012; Amorim et al., 2014; Chen et al., 2016; Pye et al., 2017).

The fact that TIMES is a bottom-up "technology explicit" model means that energy technologies (defined as any device that produces, transforms, transmits, distributes or uses energy) are deeply described by technical (i.e. useful life, efficiency, emission factors and availability) and economical (i.e. investment costs, operation and maintenance costs and variable costs) parameters.

TIMES is said to be a *partial equilibrium* model because it computes the market equilibrium only in the energy sector – in every period the quantities and prices calculated for the commodities are in equilibrium, which means that for every commodity the quantities produced by suppliers coincide with the quantities demanded by the consumers (Teotonio et al., 2017). Therefore the equilibrium takes place where the supply and demand curves intersect, from which it follows that the market prices are equal to the marginal values in the system. In TIMES detailed projections for final energy demand can be modelled and optimised jointly together with energy supply to meet this demand.

TIMES assumes competitive markets with perfect foresight – each agent has perfect knowledge of the market's current and future situation, but alone cannot affect the market equilibrium with its actions. This means that the equilibrium is calculated (and that decisions about investments and operation are taken) in just one step by maximising the economic surplus over the entire modelling time horizon. The previous assumptions ensure that when supply and demand are in equilibrium, the total economical surplus is maximised (or equivalently the net total cost is minimised). Therefore, given that the total economic surplus is the sum of the consumer's and producer's surplus, it results that TIMES looks for the configuration of the energy system that maximises social welfare (social planner point of view) (Fais and Blesl, 2015).

3.2.3.2 *Model generation, linear programming, optimisation and data handling*

TIMES is not a model itself but rather a *model generator* – all TIMES models share the same building blocks (i.e. the source code pre-defining specific constraint types, etc.),

15 For a review on different energy models refer to Jebaraj and Iniyan (2006), Connolly et al. (2010), Bhattacharyya and Timilsina (2010), Pfenninger et al. (2014) and Chiodi et al. (2015). See also section 2.2.2 on page 46.

but the in which these are structured, together with the data input by the modeller, allow for different models to be generated. The structure of TIMES is built with variables and equations that are derived from the input data. Because of the fact that in TIMES the outputs of a process are linear functions of its inputs and that also non-linear functions (such as supply and demand curves) can be represented by a stepped sequence of linear functions, it follows that in TIMES in principle all the equations are linear. This linearity property allows calculating the partial equilibrium as a linear programming problem (Tattini, 2015).

Linear programming problems aim at maximising or minimising an objective function, while respecting constraints expressed in the form of linear equations and inequalities. The canonical form for linear programming is formulated as follows:

$$\min c^T x \tag{3.13}$$

$$Ax = b \tag{3.14}$$

$$x \geq 0 \tag{3.15}$$

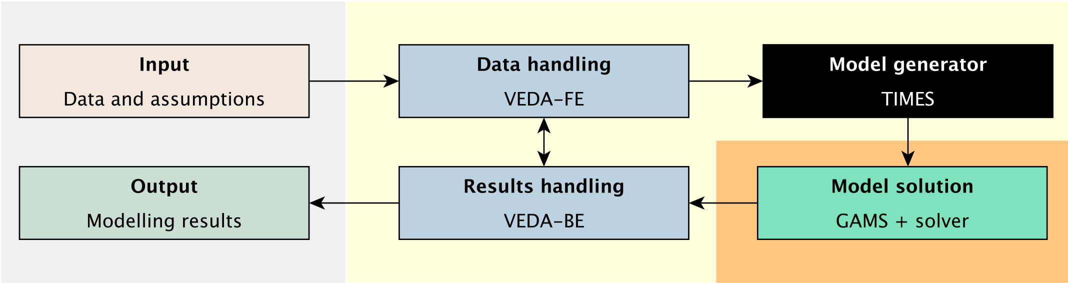
where, c and b are the known coefficients vectors, A is the known coefficients matrix, T is the transpose operator and x is the vector of decision variables (the unknowns to be determined by the optimisation). Equation 3.13 is the objective function, which expresses the criterion to be minimised. The other two expressions (Equation 3.14 and Equation 3.15) are the constraints, which are a set of equations or inequalities containing the decision variables to comply with.

TIMES' objective function is represented by the discounted sum of the annual costs of the energy system that must be minimised. First, for every year of the time horizon the sum of the costs occurred in that year is calculated. Then TIMES calculates, for every region, the total net present value, discounting all the costs of the various years to a selected reference year. They are finally summed into a single cost that is the objective function to be minimised. The mathematical expression of the objective function in TIMES is (Loulou, 2016):

$$NPV = \sum_{r=1}^{R} \sum_{y \in YEARS} \left(1 + d_{r,y}\right)^{REFYR-y} \times ANNCOST_{r,y} \tag{3.16}$$

where, NPV is the net present value for the total cost of all the regions over all years, $ANNCOST_{r,y}$ is the total annual cost in region r and year y, $d_{r,y}$ is the discount rate, $REFYR$ is the reference year for discounting, $YEARS$ are all the years over the time horizon for which there are costs, plus past years for which have been defined costs,

Figure 3.7: Overview of the VEDA system and TIMES modelling



Source: adapted from Loulou (2016)

plus years after the end of time horizon if there are dismantling costs, R is the set of regions considered in the model. The main decision variables for optimisation are the activities of the technologies, the investments in new capacity and the flows between the commodities and the processes involved in the energy system object of study.

While minimising the objective function, TIMES must also satisfy a large number of constraints expressing the physical, technological and economical relationships between the decisions variables and representing the characteristics of the energy system to optimise. In order to implement such a large scale optimisation model, TIMES uses GAMS, a high level programming language that allows solving problems with thousands of constraints and variables like those describing complex energy systems.

In order to manage a TIMES model without inputting and handling data directly in GAMS, a front-end model interface exists (VEDA-FE) for generating, modifying and running a model, and a back-end (VEDA-BE) for exploring and analysing the modelling results. The model creation process using the VEDA model interface is shown in Figure 3.7 (Loulou, 2016). The structure and data of the model are input by the modeller to VEDA-FE by means of several MS Excel workbooks. VEDA-FE recognises the information contained in the workbooks by means of special key-words and it organises them in a database.

This database is given as input to the model generator which creates files that are then translated by GAMS into a linear programming matrix containing all the coefficients in a form ready to be associated to the proper variables in the respective Equations. The last step is the optimisation – a solver (usually CPLEX) handles the matrix of coefficients and thus finds the optimal solution of the TIMES problem that represents the model. Finally GAMS generates a file that is input to VEDA-BE, the interface that allows handling the results and creating tables and graphs to analyse results.

3.2.4 *TIMES-EC – the Ecuadorean TIMES model*

3.2.4.1 *The Reference Energy System*

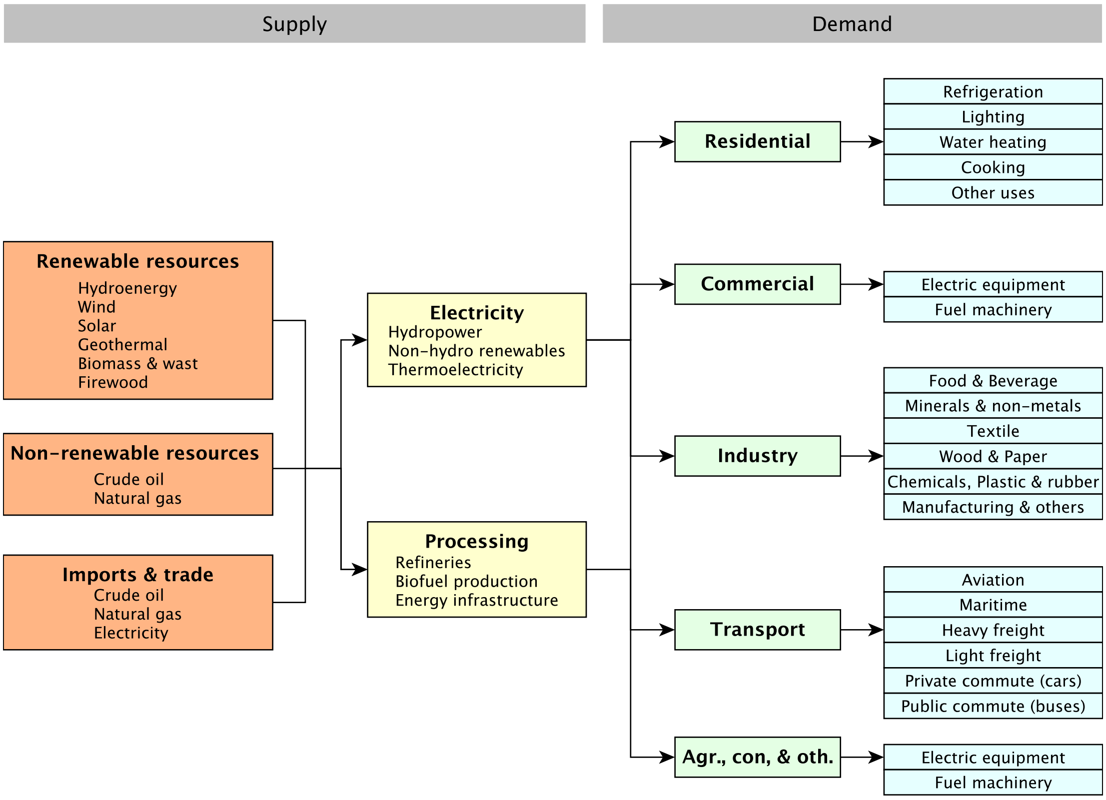
The Reference Energy System (RES) is a network description of energy flows detailing all technologies that are involved (or potentially involved) in the production, transformation and use of various energy forms. To satisfy energy demand services required by economic activities, demand devices/technologies that transform energy commodities into useful demands are used. Storable energy commodities, like gasoline and diesel fuels are produced by processes technologies while non-storable energy forms like electricity and heat are generated by conversion technologies. Processes and conversion technologies use primary energy forms obtained from primary energy resource technologies or secondary energy forms, which themselves have been produced by previous processes.

Figure 3.8 on the following page shows a highly simplified RES of the Ecuadorian energy system used in TIMES-EC. Conversion technologies and processes are represented by boxes, while energy commodity flows are the lines interconnecting the boxes. TIMES-EC has ten sectors, divided into five supply side and five demand sectors:

1. Supply sectors:
   a) Renewable resources: domestic renewable resources
   b) Non-renewable resources: extraction infrastructure
   c) Imports and trade: fuel and electricity trading
   d) Processing and infrastructure: Refineries, biofuel production and energy infrastructure
   e) Electricity: Electricity generation and transmissions and distribution grids.
2. Demand sectors:
   a) Residential
   b) Industry
   c) Commercial
   d) Transport
   e) Agriculture, construction & others

Each element in the network is characterised by input parameters that define the main components in the system: energy service demands, regional resource potential

Figure 3.8: Simplified RES of the Ecuadorian energy system in TIMES-EC



and costs, technology data and scenarios to explore different policies. An overview of the inputs and outputs of TIMES-EC is depicted in Figure 3.9 on the next page.

TIMES-EC has the following inputs:

1. End-use energy demand drivers, which are quantified endogenously based on the evolution of exogenously defined socio-economic drivers (e.g. population and GDP) and demand sensitivities in five end-use sectors;

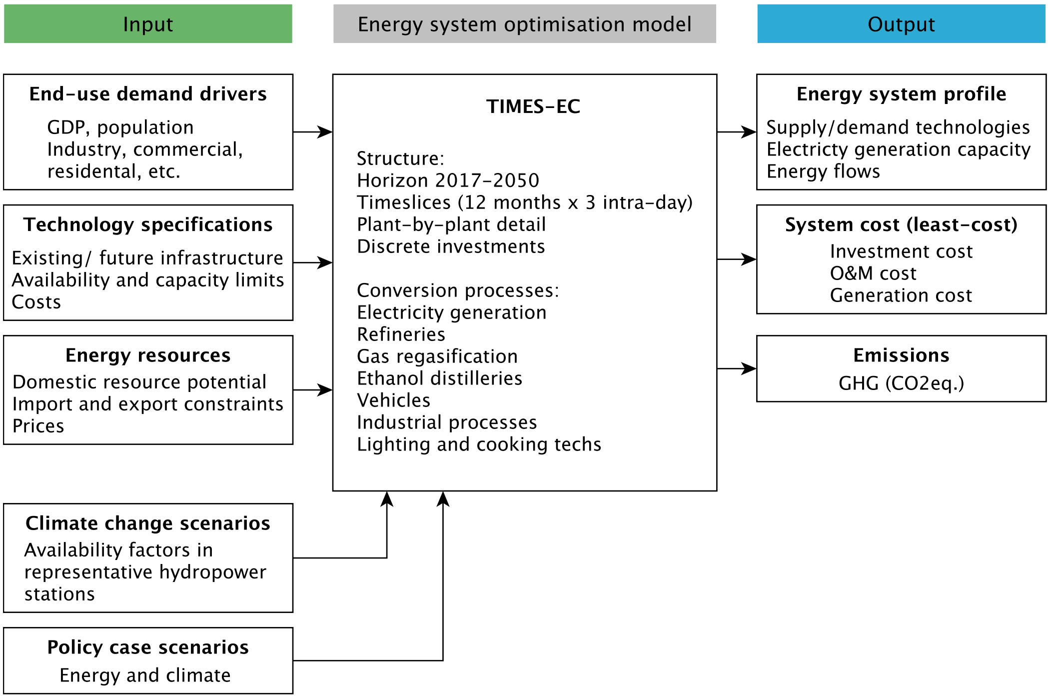
2. Technological specifications, provided by a comprehensive database of technical and cost data for existing and future energy conversion technologies (efficiency, capacity, availability, lifetime, lead-time, investment costs, and fixed and variable O&M costs);

3. Energy resources, including domestic renewable (solar, wind, biomass, geothermal and runoff) and non-renewable (oil and gas) potential and the prices of imported electricity and fossil fuels;

4. Climate change scenarios, which are defined by the hydrological assessment;[16] and,

16 Climate change impacts are limited in this analysis to their effect on hydropower supply; possible impacts on other parts of the energy system, such as changes to wind and solar resources, changes to thermal efficiency and the associated de-rating of power plants, and possible changes to energy demand (e.g. heating/cooling), are not accounted for and should be included in further research.

Figure 3.9: Inputs and outputs of TIMES-EC



5. Policy cases, which reflect possible evolutions of the deployment of hydropower according to national energy and environmental policy choices.

The key outputs of TIMES-EC include:

1. Energy system profile, including installed capacity and energy flows per technology;
2. Total energy and electricity system costs; and,
3. Energy related GHG emissions.

Depending on the energy system studied, the RES may cover the whole energy system, showing how primary sources are extracted, then transformed by conversion processes into other commodities, afterward transported and finally consumed by end-use devices. This would render a fully described energy system, but it is not compulsory. In fact, the RES and the associated energy system model could just focus on the description of some sub-sectors of the total energy system. The TIMES-EC model represents the whole energy system but for purposes of this thesis, it depicts the power sector in greater detail than others.

Existing installed electricity generation capacity between 2014–2017 are model inputs and have been modelled at the plant level (over 125 plants, MEER, 2017a), whereas the long-term capacity expansion (over 20 new technology options) until 2050 is a model output. The characterisation of new electricity generation technologies, as cost data, availability and efficiencies, is input to the model based on a range of sources (?IRENA, 2015b; NREL, 2016; IEA, 2016b) and the specific observed costs of plants installed in Ecuador during the last decade (MEER, 2017a), as can be seen in Table 3.11 on page 137. The general annual discount rate is set to 8%, as used in strategic planning by the Ecuadorian Central Bank (BCE, 2017). In practice, different electric generation alternatives face different financing conditions. Technology-specific discount or hurdle rates is a way to capture higher risk primes for riskier technologies (Decarolis et al., 2017). The attempt to reproduce these differences will be approached by including their risk with a portfolio theory approach (explained in Section 3.3).

3.2.4.2 *Time slices, periods and model horizon*

In every TIMES model a time horizon must be indicated. Such time horizon is then divided into various time periods composed by a certain number of years that can also vary from period to period. Usually the first period consists of one single year, of which all the information and values of parameters are known, in order to provide a proper description of the reference scenario and to facilitate the calibration of the model. Then the following time periods have increasing time length. Time periods can be further subdivided into smaller time periods called time slices. They are used for representing commodities whose characteristics (for instance, availability and load) vary sensibly within the year (e.g. electricity and solar energy).

The base year of TIMES-EC is 2014 and the modelling horizon is until 2050.[17] The periods from 2014 to 2017 serve as calibration years, for which statistical values regarding energy imports, exports and sector demand were taken from the Ecuadorian National Energy Balance 2015 (MICSE, 2015). Disaggregated installed capacity and power generation was obtained from the Multi-annual Statistics Report of the Ecuadorian Power Sector 2016 (ARCONEL, 2016).

Each model time period is divided into 36 time-slices, with 12 months in a year, each with a single representative day composed of three periods: morning (8 hours), day (12 hours) and night (4 hours-peak). Table 3.7 shows the time slice representation in TIMES-EC. This time-slice structure is appropriate to study the long-term energy system expansion from an energy balance perspective (further details on daily load profile can be found in Section 3.2.7 on page 138). Specifically, it was chosen to capture the monthly and diurnal characteristics of hydropower generation and end-use power de-

17 The model has actually been expanded up to the year 2085 to capture effects of the long operational life of hydropower (75 year) and also the effects of uncertainty in precipitation towards the end of the century derived from long-term climate data (up to 2100). The long-term horizon taken in the model also ensures that the lock-in effect of capital stock inertia associated to near-term policies is avoided (Vogt-Schilb et al., 2014; Bertram et al., 2015; Riahi et al., 2015).

Table 3.7: Time slice representation in TIMES-EC

Season	Intra-day period	Time represented	Notes
January (JAN)	Morning (M)	23:00 - 7:00	Lowest demand
February (FEB)	Day (D)	7:00 - 19:00	Intermediate
March (MAR)	Night (N)	19:00 - 23:00	Peak demand
April (APR)			
May (MAY)			
June (JUN)			
July (JUL)			
August (AUG)			
September (SEP)			
October (OCT)			
November (NOV)			
December (DEC)			

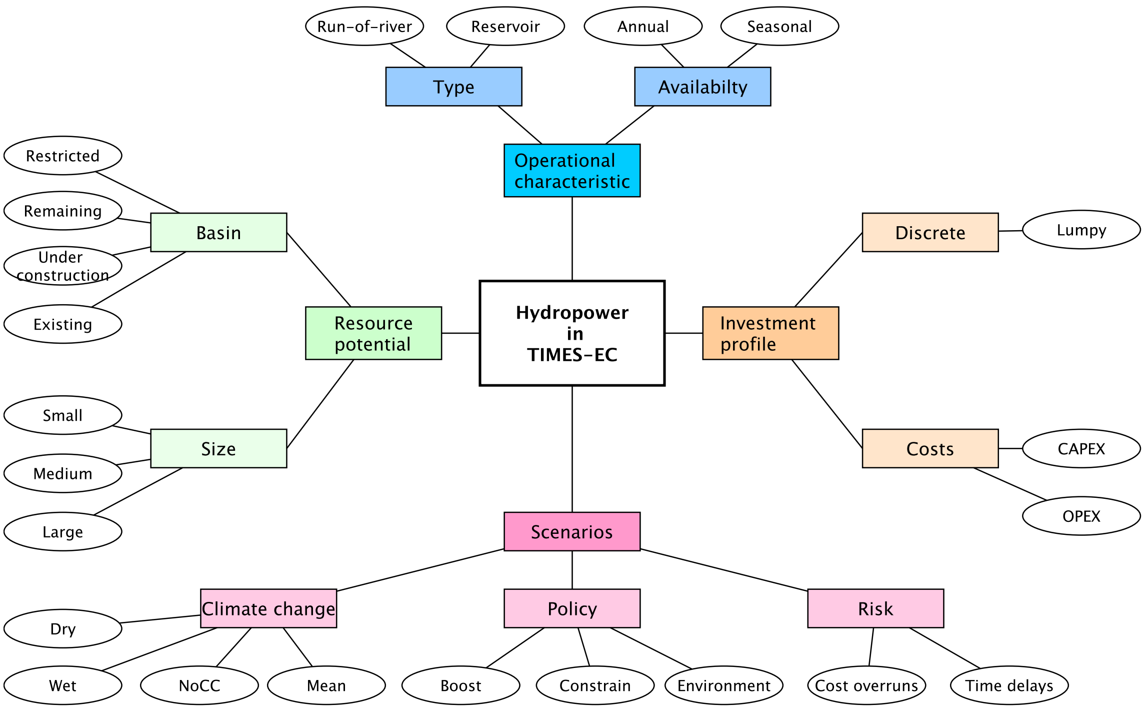
mand respectively; and is thus aligned well with the data used in this study. Investment decisions are made for each model period and operational decisions are made for each time-slice level, both under perfect foresight over the whole model horizon.

3.2.4.3 *Geographic region*

A TIMES model may include different regions. In such case, each region is described by its own RES and the interconnections between the regions can be described separately. The TIMES-EC model has one region. The main reason to work with a single-region model in TIMES-EC is that the model was created mainly to represent a single transmission system (SNI), which remains the core and the focus of the analyses. The single-region modelling of Ecuador's power sector is adequate to analyse the global electricity supply and future capacity capacity expansion which will most likely be interconnected to the SNI. Another important reason was the difficulty to find data related to the single regions within Ecuador – some of this information is held by the National Electricity Regulation and Control Agency (ARCONEL), but significant information is completely missing so that too many assumptions would have been necessary.

Although the model has only one region in terms of geographical regions, six hydrographic regions have been defined to capture the differences of hydrology among Ecuadorian watersheds and river basins (detailed further in section 3.2.5). A further improvement of the model would be to disaggregate electricity supply and consumption in at least three regions, detailing the Coast, Highlands and the eastern Amazon region, and to integrate them in a final three-region model.

Figure 3.10: Hydropower modelling in TIMES-EC



3.2.5 *Hydropower modelling*

Given the focus of this research, the description of hydropower in the TIMES-EC has been done with particular detail. The following characteristics of hydropower have been defined to capture its expansion and operation as best as possible:

1. Resource potential,
2. Operational characteristic,
3. Investment profile, and
4. Scenarios of climate, policy and risk.

Figure 3.10 shows the level of detail of hydropower's characterisation in TIMES-EC, which w ill be explained in the following paragraphs.

3.2.5.1 *Hydropower potential*

Hydropower potential in Ecuador is located in six large river basins, as can be seen in Figure 3.11 on the next page. The largest hydropower stations as of December 2017, which together account for about 85% of the total hydropower installed capacity, are shown in Table 3.8 on the facing page (MEER, 2017a). The Ecuadorian Electricity Master Plan (PME) estimated the total techno-economically feasible hydropower potential to be

Figure 3.11: Ecuador's six major river basins and geographical distribution of the Government's assessment of hydropower potential (GW)

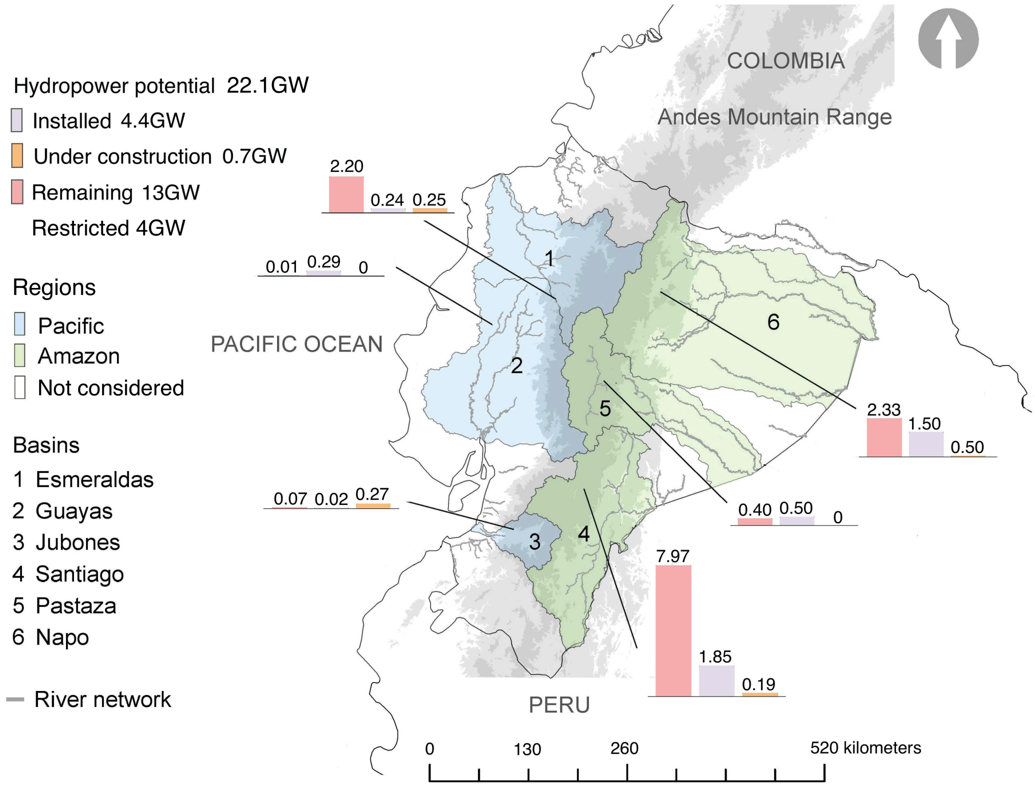
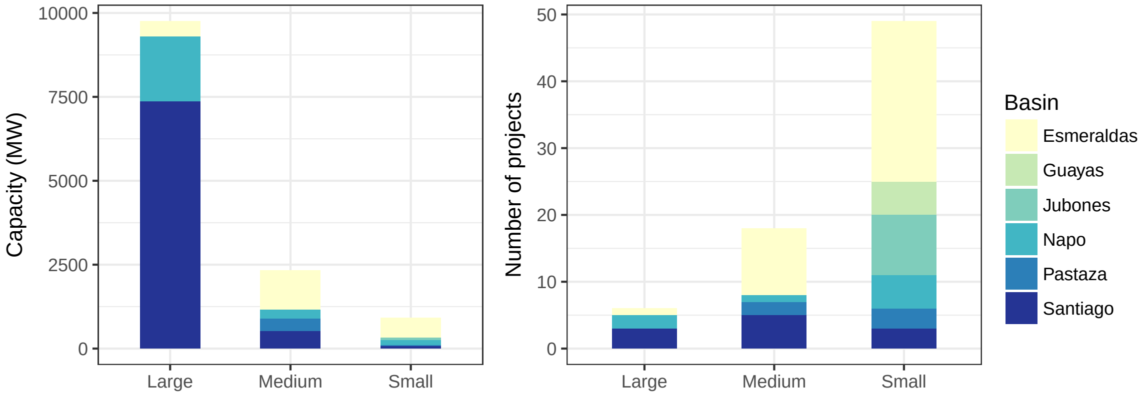


Table 3.8: Largest hydropower stations in Ecuador as of December 2017

Power station	Basin	Type	Installed capacity (MW)
Coca Codo Sinclair	Napo	ROR	1,500
Paute[a]	Santiago	DAM	1,100
Sopladora[a]	Santiago	DAM	487
San Francisco[b]	Pastaza	ROR	212
Marcel Laniado	Guayas	DAM	170
Mazar[a]	Santiago	DAM	170
Agoyan[b]	Pastaza	ROR	156
Total largest hydro			3,795
Total Ecuador hydro			4,486

Note: Hydropower stations with matching superscripts belong to cascading systems.
Source: ARCONEL (2018b)

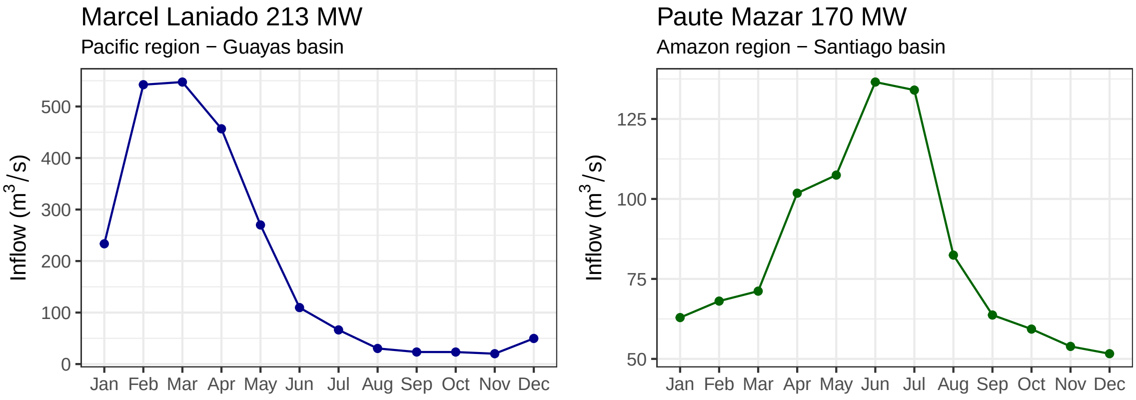
Figure 3.12: Remaining hydropower potential and number of projects



22.1 GW (ARCONEL, 2015), which is composed of 4.4 GW that are already installed, 0.7 GW that are under construction, 13 GW that are untapped and are viewed as technologically feasible and cost effective to deliver, and an estimated 4 GW that are likely to encounter development restrictions due to environmental conservation concerns, social problems and accessibility issues, all of which led the Government to conclude that these resources are unlikely be utilised in the future (ARCONEL, 2015). The Santiago and Napo river basins are especially relevant in terms of hydropower generation, holding most of installed capacity and the largest hydropower systems in the country. The largest hydropower stations in each of these basins will be used as representative for each river basin, as has been explained in Section 3.1.3 on page 99.

To assess remaining potential, this study has used the hydropower project inventory that is presented in the Electricity Master Plan (PME) (MEER, 2017a) to represent the remaining potential for new hydropower capacity expansion in Ecuador (totalling 13 GW). This has been categorised according to the river basin in which each envisioned project is located and further divided into three capacity sizes: small (1 to 50 MW), medium (50 to 450 MW) and large (>450 MW). In total, 73 projects have been categorised, of which six are large (totalling 9,756 MW), 18 are medium (totalling 2,327 MW) and the remaining 49 are small (totalling 917 MW). The distribution of the total remaining capacity of different sizes and the total number of projects is shown in Figure 3.12. Notice the inverse correlation between capacity and number of projects – most of the remaining potential is concentrated in large scale projects. The Santiago, Napo and Esmeraldas basins hold the majority of remaining potential in large and medium sized projects, while the Guayas, Jubones and Pastaza basins have only the potential for medium and small sized projects. For the detailed list of hydropower projects included in the model, please see Table A.1 on page 289 and Table A.2 on page 291 in Appendix A.

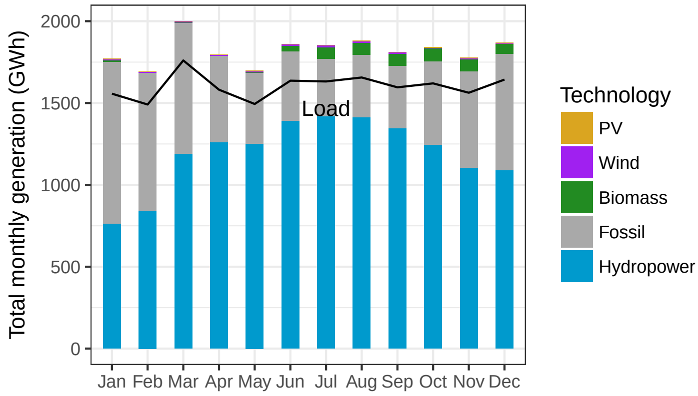
Figure 3.13: Ten-year (2006-2015) average monthly inflow for hydropower stations in different watersheds



In order to have an adequate representation of hydroelectric power generation, it is of primary importance to understand the water availability into hydropower stations and, more in general, the Ecuadorian hydrologic system, as has been detailed in Section 3.1.3 on page 99. Hydrological regimes vary between Ecuadorian basins but particularly between the Pacific and Amazon regions. For basins that are in the Pacific region (Esmeraldas, Guayas and Jubones) to the West of the Andes mountains, runoff shows a characteristic seasonal behaviour with higher flows between January and May (wet season) and low flows occur between June and December (dry season). For basins that are in the Amazon region (Santiago, Pastaza and Napo) to the East of the Andes, runoff is slightly offset with higher flows registered between April and August and low flows between September and March. Figure 3.13 shows the ten-year (2006-2015) average monthly inflow to the reservoirs of hydropower stations Marcel Laniado (213 MW) in the Pacific region and Mazar (170 MW) in the Amazon region.

As hydroelectric power plants are, in general, distant from large consumption centres, there is a need to transmit electricity through the integrated SNI. Although this incurs in transmission losses, it facilitates, on the other hand, integration between hydropower systems and increases the quantity of energy that can be obtained from the hydroelectric system. This integration of the SNI allows the electricity system to be operated according to the regional differences of water availability, taking advantage of seasonal complementarity among basins between the months of January to August. However the months of November to February are coincident low flow seasons for basins in both regions and represent a critical period for power generation. This can be seen in Figure 3.14 on the next page, where total monthly generation together with the average power demand in Ecuador throughout 2016 is shown. Fossil fuel-based generation complements hydropower generation, specially during the months of November, December,

Figure 3.14: Monthly generation and electricity load in Ecuador in 2016



January and February. On the contrary, from March to September, there is more water availability and the share of thermal electricity is reduced. Power demand does not vary strongly between seasons (see Section 3.2.7 on page 138).

In this sense, the analysis of climate change impacts and adaptation strategies must be carried out in an integrated fashion. As mentioned in Section 2.2.2 on page 46, the characteristics of hydroelectric systems have influence on the definition of the methodology used in the hydrological and energy modelling. For the Ecuadorian case, the modelling tools used need to incorporate various aspects of this integrated complexity. Therefore, in this study, an integrated analysis of the SNI has been performed, in which the projected generation for each hydropower plant (each basin) is the result from its participation within the integrated power system. Similarly, least-cost strategies for adaptation consider the integration of hydroelectricity with other generation sources and the various repercussions in other segments of the energy sector.

3.2.5.2 *Hydropower technology*

Modelling hydropower in TIMES-EC required a major effort with respect to other power generation forms. In fact, in order to give a proper description of such technology, it was necessary to represent the operation logic of run-of-river (ROR) and reservoir-based (DAM) technologies according to water inflow availability.[18] In TIMES the maximum yearly activity of a process is computed by the following equation:

$$ACT = CAP \times AF \times CAP2ACT \tag{3.17}$$

18 Our assessment did not consider pumped storage hydropower because of their greater impact on the landscape and flow regime and because they are generally more expensive as they require larger dams and reservoirs. Reasons to build these systems are dependent on local social and economic conditions, which were outside the scope of our assessment (Gernaat et al., 2017).

where ACT is the process activity (which unit in TIMES-EC is PJ), CAP is the installed capacity of that process (expressed in MW), AF is the availability factor[19] and $CAP2ACT$ is a parameter used to bring the two terms of the equation to the same unit (in this case it is 31.536 to transform from GW to PJ).

From Equation 3.17 it follows, that in TIMES, a possible way to describe the activity of a process is by defining its availability factor in the various time slices. Even though this technique allows modelling a complicated feature in an simplified manner, the definition of the availability factors in every time slice increases the model size. The implementation of this technique to model hydropower is particularly beneficial. Since hydropower is a renewable form of power generation and the conversion efficiency from primary energy to electricity of such type of plants in TIMES can be set equal to 1, putting a constraint on the output commodity (electricity) from a process is equivalent to putting it on the input commodity (water) (Tattini, 2015).

Therefore in TIMES-EC the production from hydropower (both ROR and DAM) has been modelled by describing, for every monthly time slice, the availability factor of the commodity electricity (ELC) coming out from such plants. This artifice allows modelling hydropower generation by describing the power production rather than the water inflow to the hydropower stations. In addition, ROR and DAM have been modelled with different types of availability factor attributes that TIMES offers to further specify how the availability factor is to be implemented, as has been detailed in Table 3.16 on the following page and has been exemplified in Figure 3.15 on the next page.

To represent run-of-river (ROR) plants that feature inflexible electricity production, an availability factor according to monthly inflow patterns (termed AF in the model code) has been used. This availability factor attribute allows ROR to have certain flexibility within the daily time slice but no flexibility at the seasonal (monthly level). Thus, indicating that there is no possibility for inter-seasonal storage of water. For ROR the seasonal availability factor represents an electricity generation profile that is the same as the water inflow profile. The seasonal availability factors for ROR plants have been determined in the hydropower modelling of representative ROR hydropower stations as explained in Section 3.1.2 on page 97.

In the case of flexible reservoir (DAM) plants, an annual availability factor (AFA in the model) that constrains the total level of annual electricity generation is used to represent the inter-seasonal storage capacities of this type of hydropower. This attribute allows

19 Capacity factor is the simplest way to measure the energy delivered by the power station during a year, when compared to the case of it working at full capacity. The availability factor in TIMES, however, is a way of further detailing how energy can be supplied within time slices and allows to model the flexibility of electricity supply technologies further.

Figure 3.15: Example of availability factor attributes used in TIMES-EC to model hydropower

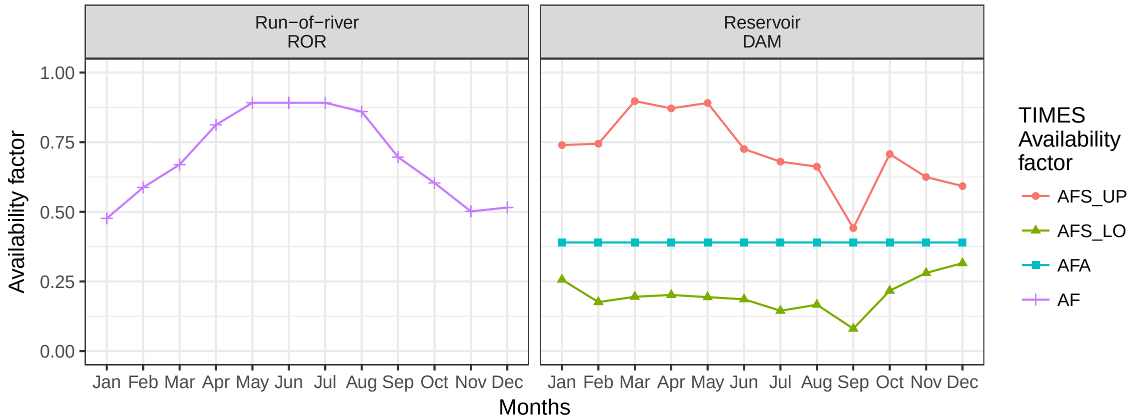


Figure 3.16: Availability factor attributes used in TIMES-EC to model hydropower

Hydropower type	TIMES Attribute code	Description
ROR	AF	Seasonal availability factor according to monthly simulated electricity production.
DAM	AFA	Annual availability factor according to annual simulated electricity production.
	AFS_LO	Seasonal availability factor with upper limit according to the lowest monthly production according to historical data.
	AFS_UP	Seasonal availability factor with upper limit according to the highest monthly production according to historical data.

the model to endogenously allocate electricity in different seasons as long as the annual availability is complied with.[20] Moreover, a variable seasonal availability factor (AFS_UP and AFS_LO in the model) with maximum and minimum production levels according to historical data, is used to constrain seasonal electricity generation to respect maximum and minimum environmental flows according to historic data. The annual availability factors for DAM plants have been determined in the hydropower simulation model of representative DAM hydropower stations as explained in Section 3.1.2 on page 97. For these stations, the hydropower modelling in Section 3.1.2 on page 97 allowed to estimate the annual availability factor considering that water could be stored and used during the next period. Spillage only occurs if the reservoir is full, therefore excess water from one month can be used during the following.

The availability factor approach to model hydropower has been used in several studies using TIMES. Kannan and Turton (2014) model the Swiss electricity sector and characterise hydropower by defining four seasonal availability factors (for Spring, Summer, Autumn and Winter), using maximum and minimum availability factors for DAM hydropower plants and only maximum availability factor limits for ROR. In a similar approach Seljom and Tomasgard (2017) define four seasonal availability factors by using maximum and minimum values from historic records for the Norwegian hydropower system. However, aggregating the year into four seasons does not allow to assess particularly dry months during the year where other means of generation might be needed. In any case, this might not be so important for Switzerland or Norway, which are strongly interconnected with the rest of Europe and can withstand low flow seasons with imports. Thus this might not be the case for Ecuador, or other countries that have limited interconnection capacity, and low flow season will require to be solved domestically with alternative sources. In this study a monthly resolution will be used which better captures critical low flow months. This is also consistent with the monthly GCM output that has recently been made available (see Section 3.1.3 on page 99).

3.2.5.3 *Hydropower investment and retirement*

The TIMES model's discrete investment feature for new capacity additions is used to model the lumpy investment characteristics of medium and large hydropower projects, while investments in small hydropower are treated in a linear fashion. This approach reflects the criteria that in a given large river scheme only a corresponding large facility would make technical and economic sense, and the fact that large hydropower projects

20 In practice, the availability of reservoir hydropower may change due to evaporation and other loses if the water is stored for a longer period. However evaporation from reservoirs has not been considered in this study.

Table 3.9: Discrete investment steps according to hydropower plant size and river basin

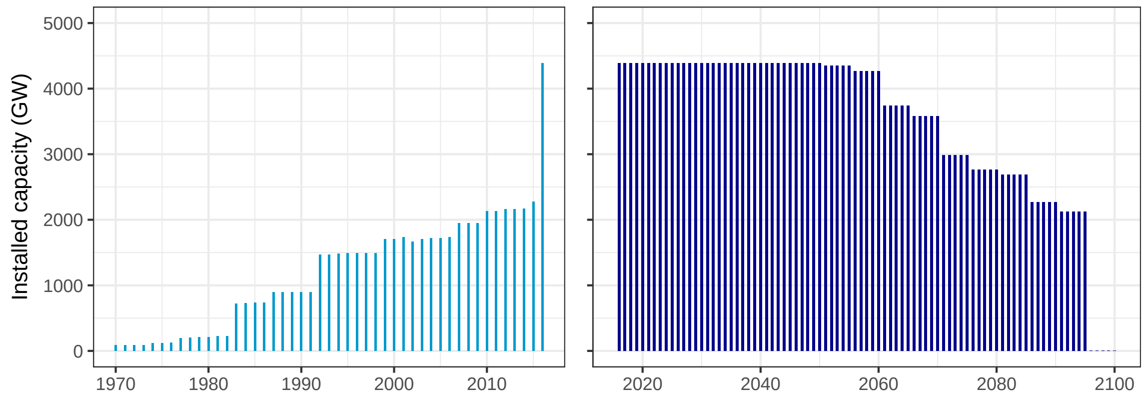
Region	Basin	Discrete investment step (MW)	
		Medium (50-450MW)	Large (>450MW)
Pacific	Esmeraldas	100	460
	Guayas	-	-
	Jubones	-	-
Amazon	Santiago	100	1,200
	Pastaza	180	-
	Napo	270	1,000

are almost always built in consecutive stages that accompany demand growth and financing capacity of the operator (OECD/ECLAC/CAF, 2015).

The model can endogenously choose to invest in large and medium hydropower capacity in discrete steps according to the potential and the number of projects in each of the six river basins (as seen in Figure 3.11 on page 125 and Figure 3.12 on page 126). For example, the Santiago river basin shows a significant potential of almost 8 GW, however most of it is concentrated in two large capacity facilities, namely the Santiago-G8 (3,600 MW) and the Zamora (3,180 MW) projects (CELEC, 2017). To reflect this, the model is constrained to invest in steps of 1,200 MW for large hydropower in this basin, as it is assumed that these projects would be built in three stages each. Table 3.9 shows the discrete investment sizes (in MW) for different basins. The model will endogenously pick to invest on the deployment of hydropower according to basin, size type and cost of the projects made available. The details of hydropower costs for different types and sizes can be found in Table 3.11 on page 137. Hydropower costs depend on size, and electricity cost on the corresponding availability factor, there has not been made any differentiation to consider different prices in different basins. It is too difficult to know what the costs of roads and other additional infrastructure for the projects.

The retirement profile of existing hydropower stations has been computed from the annual installed capacity and hydropower plant lifetime. First, the annual installed capacity profile was determined for the period 1970 to 2016 (OLADE, 2017a), which can be seen in Figure 3.17 on the facing page. Next, it is assumed that hydropower plant lifetime is 75 years (IRENA, 2012b) and that after this time hydropower stations are removed from total installed capacity. However, given that most of the installed capacity in Ecuador was installed in the mid 1980s, only 50 MW, which was installed before 1975, is anticipated to be retired before 2050. The retirement profile of existing

Figure 3.17: Hydropower installed (left) and retirement profile in Ecuador for existing installed capacity



hydropower plants for the period 2016 to 2100 is shown in Figure 3.17 and has been an input to the model.

3.2.5.4 *Scenarios*

This analysis specifically focuses on the impacts and uncertainties surrounding hydropower resource potential, as these effects are expected to dominate the future Ecuadorian energy system. To characterise climate change uncertainty, the results from the hydrological modelling detailed in Section 3.1 on page 91 will be used, in which long-term scenarios of representative hydropower availability factors are projected for six river basins in Ecuador as detailed in Section 3.1.4 on page 108. These availability factors are an input into TIMES-EC as has been explained in previous paragraphs and climate scenarios have been detailed in Table 3.4 on page 108. Regarding policy cases that impact the development of hydropower technology, this will be explained in greater detail in Section 3.2.10 on page 151. In addition, the uncertainty of capital cost overruns of hydropower infrastructure will also be considerd in the constuction of risk scenarios, which will be further explained in Section 3.3 on page 159.

3.2.6 *Other generation technologies modelling*

3.2.6.1 *Solar and wind*

Intermittent solar PV and wind power has been modelled similar to run-of-river hydropower. The Renewables ninja online tool from Pfenninger and Staffell (2016); Staffell and Pfenninger (2016) was used to run simulations of the hourly power output for solar photovoltaic power plants and wind farms located in high potential regions according to the Ecuadorian Wind Atlas (MEER, 2013) and Solar Atlas (CONELEC, 2008). These results were then translated into aggregated availability factors for each of the 36 time slices of TIMES-EC. The variability of solar plants and wind farms was considered through their peak load contribution (capacity credit);[21] assumed to be 0% and 20%, respectively (Mills and Wiser, 2012; Holttinen et al., 2016; IRENA, 2017). The details of considered PV, CSP and wind technologies can be seen in Table 3.11 on page 137. Only on-shore wind capacity for different wind potentials (7 to 8.5 m/s) has been considered with long-term cost descending according to the projections of IEA (2015). Both centralised and distributed PV solar farms have been considered, as well as concentrated solar power (CSP) with 12 hours of thermal energy storage, which investment cost have been defined according to projections from IEA (2014c); Soria et al. (2016); Fichter et al. (2017).

Figure 3.18 on the facing page shows simulated hourly and monthly availability factors for a typical photovoltaic plant in Ecuador. Average annual availability factor for a typical photovoltaic plant is 0.18. Figure 3.19 on the next page shows simulated hourly wind farm availability factors for a 5-year time series (2011-2106), which shows a seasonal pattern with high production between May and October and low winds between November and April. Figure 3.20 on the facing page shows average monthly availability factors for a range of wind speeds that have been calculated based on the wind potential registered in the Ecuadorian Wind Atlas (MEER, 2013) and respecting the seasonal patterns obtained with the simulated hourly values. Table 3.10 on page 136 shows the potential and annual generation ranges according to the Wind Atlas. Annual availability factor for a typical wind farms ranges from 0.20 to 0.34, depending on the annual average windspeed. It is assumed that wind power potential is not increased or decreased due to climate change. The changes in climate model wind speeds, from the control to the scenario period, have shown to be small, with values within the natural climate variability range (see Section 2.2.1 on page 35). However, lack of horizontal resolution and a detailed description terrain in GCMs, would possibly underestimate impacts, this has also been the assumption of previous studies assessing wind energy in long-term energy models (De Lucena et al., 2010b; Seljom et al., 2011).

21 The capacity credit is the peak demand less the peak residual demand, expressed as a percentage of the variable renewables installed (IEA, 2011).

Figure 3.18: Simulated availability factors for photovoltaic plants at the inter-day and inter-annual time scale in Ecuador

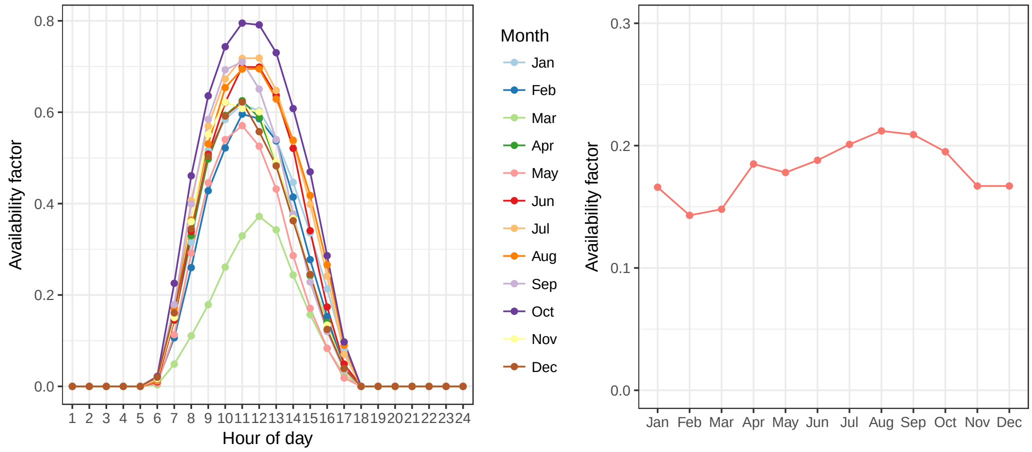


Figure 3.19: Simulated hourly availability factors for a wind farm in Ecuador

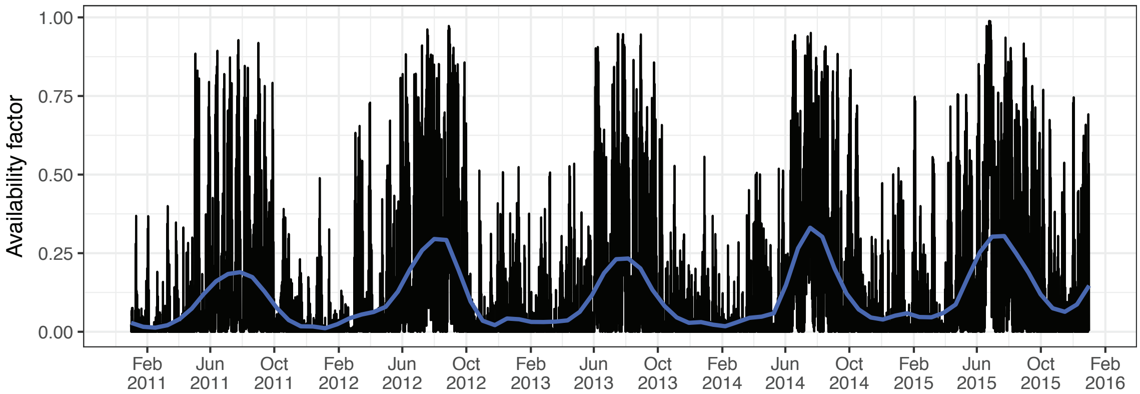
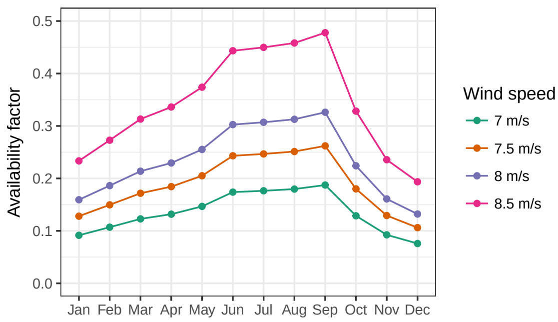


Figure 3.20: Monthly availability factors for different wind speeds in Ecuador



3.2.6.2 *Fossil fuel, geothermal and biomass thermal generation*

Thermal power plants (using natural gas, oil products, biomass, biogas and geothermal) for different technology types (steam turbine, combined cycle gas turbine, open cycle gas turbine and internal combustion engine) are included in the model, making them available for the whole year. The differences among thermal power plant technologies have been modelled through their efficiencies and availability factors which can be seen in Table 3.11 on the next page. All thermal technologies have capacity credits of 100% allowing them flexibility to cover peak loads since these technologies have low minimum loads and a quick start up time (Welsch et al., 2014; Poncelet et al., 2016; IRENA, 2017), except CSP, which has 50% capacity credit. The efficiency values and the availability factors for existing fossil power plants were mainly taken from ARCONEL (2018a). Technical details for new thermal plants can be seen in Table 3.11 on the facing page.

The investment costs for thermal technologies depend on fuel and technology. Direct-combustion of biomass is paired with steam turbines (Rankine cycle) while biogas produces electricity with internal combustion engines using landfill gas. Natural gas powers open (Brayton cycle) and combined cycle (Brayton + Rankine) gas turbines. The upgrade of these technologies has also been considered with carbon capture and storage (CCS) technologies.[22] Investment costs of these technologies follow slight decreases according to projections of ?GCI (2016); IEA (2016b).

The deterministic approach of perfect foresight of long-term electricity infrastructure costs and fossil fuel prices has also been assessed in this thesis and section 3.3 will present a methodology to treat this uncertainties in the context of TIMES-EC.

22 Retrofitting of CCS technology in current gas power plants and the corresponding reduction of efficiency for the power plant is not considered due to the size and age considerations according to IEA (2016c).

Table 3.10: Ecuadorian wind potential according to average wind speed

Average wind speed (m/s)	Power (MW)	Generation (GWh/year)	Availability factor
>7	1671	2869	0.20
>7.5	930	1996	0.24
>8	500	1287	0.30
>8.5	275	826	0.34

Source: MEER (2013)

Table 3.11: Summary of techno-economic characterisation of selected power generation technologies included in TIMES-EC

Source	Technology name	Vintage year	Investment cost (US$/kW)	Fixed costs (US$/kW)	Variable costs (MUS/kWh)	Efficiency (%)	Life time (Years)	Lead time (Years)	Availability factor (%)	Capacity credit (%)
Hydro[a]	ROR Small	2015	3,297	66			75	4	According to hydrological scenario	75
		2050	3,297	66						
	ROR Medium	2015	2,513	50			75	6		75
		2050	2,513	50						
	ROR Large	2015	2,100	42			75	8		75
		2050	2,100	42						
	DAM Medium	2015	3,166	63			75	6		90
		2050	3,166	63						
	DAM Large	2015	2,646	53			75	8		90
		2050	2,646	53						
Wind[b]	Wind onshore	2015	2,530	38			25	2	13-34	10-30
		2050	1,158	17						
Solar[c]	PV-US	2015	1,942	20			30	2	18	0
		2050	852	10						
	PV-DG	2015	2,680	27			30	2	18	0
		2050	1,240	12						
	CSP with 12-hr TES	2015	7,254	145			30	4	42	50
		2050	4,422	88						
Biomass[d]	Bagasse with CEST	2015	2,712	95		35	30	3	78	100
		2050	2,392	84						
	MSW gas	2015	2,350	94		32	20	2	58	100
		2050	2,250	90						
Geothermal[e]	Geothermal	2015	5,855	117		85	30	4	85	100
		2050	4,424	88						
Natural gas[f]	OCGT	2015	869	22	0.2	35	25	3	85	100
		2050	744	19	0.2	38				
	CCGT	2015	1,190	24	0.2	58	25	3	85	100
		2050	913	18	0.2	61				
	CCGT w/CCS	2020	2,450	86	0.3	51	25	4	70	100
		2050	2,450	74	0.3	53				
Diesel[f]	ICE	2015	1,000	15	0.1	39	20	2	85	100
		2050	1,000	15	0.1	39				
HFO/RFO[f]	ST	2015	1,770	44	0.1	39	30	3	85	100
		2050	1,770	44	0.1	39				
HFO/RFO[f]	ST w/CCS	2020	4,500	180	0.3	32	30	3	75	100
		2050	4,100	164	0.3	36				

*Notes: Efficiency of renewable energy technologies (except biomass) is considered to be 100% since primary energy resource conversion (solar, wind, hydraulic head, etc.) is not accounted for in the model. ROR: Run-of-river hydropower, DAM: Reservoir hydropower, PV-US: PV utility scale, PV-DG: PV distributed generation, CSP: Concentrated Solar Power, TES: Thermal energy storage, MSW: Municipal solid waste, CEST: Condensing extraction steam turbine, OCGT: Open cycle gas turbine, CCGT: Combined cycle gas turbine, HFO: Heavy fuel oil, RFO: Residual fuel oil, ST: Steam turbine, ICE: Internal combustion engine. Sources:[a]MEER (2017a); Teotonio et al. (2017),[b]Daly and Fais (2014); IEA (2016b),[c]NREL (2016); Fichter et al. (2017); IEA (2014c),[d]NREL (2016); IRENA (2012a); Fichter et al. (2017),[e]NREL (2016); IRENA (2015b),[f]?GCI (2016)

3.2.7 *Demand and drivers*

3.2.7.1 *Drivers*

The future socio-economic evolution of Ecuador and the associated final energy demand projections are the driving forces of the whole energy system modelled in TIMES-EC. Population and gross domestic product (GDP) figures for Ecuador up to 2050 are based on the Shared Socioeconomic Pathways SSP2 narrative developed by the Institute for Applied System Analysis (IIASA) (Riahi et al., 2017). The SSP2 depicts a world in which social, economic, and technological trends do not shift markedly from historical patterns.[23] The selection of the middle-of-the-road scenario also fits well with the RCP4.5, which is also considered to be an intermediate mitigation scenario. Figure 3.21 on the next page shows IIASA's five SSP scenarios for GDP and population for the 2020–2050 period.[24] Details for population and GDP for selected milestone years between 2017 and 2050 are shown in Table 3.12 on the facing page.

It is assumed that Ecuador's population will increase from 16.7 million people in 2017 to 21.5 million people in 2050. Population annual growth rate increases up to 2020, after which it declines gradually, showing a slow down in population growth during 2030 to 2050 (Table 3.12 on the next page). Estimations of future economic growth are much more uncertain than future population growth, as can be seen in Figure 3.21 on the facing page. The average Ecuadorian household consisted of 3.5 persons per household in 2015, while in 2050 it is assumed to be 2.8 persons per household, according to INEC (2017).

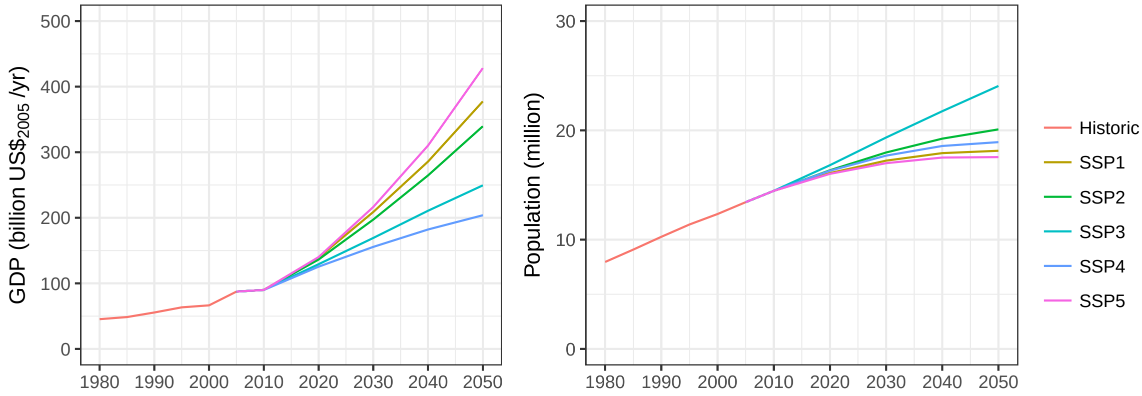
Economic evolution follows the Central Bank of Ecuador's projections until 2020 (BCE, 2017), which accounts for the recent economic crisis effects due to low oil prices (2014 – 2015). After 2020, GDP figures from the SSP2, which assumes that per-capita income levels grow at a medium pace on the global average, with slowly converging income levels between developing and industrialised countries. GDP is assumed to roughly triple from US$ 127 billion in 2017 to US$ 340 billion in 2050, which means a fairly consistent average annual growth of 2.7% during the modelling horizon.

According to the projections of population, households and GPD, five demand drivers have been defined: population (POP), gross domestic product (GDP), number of households (HSH), GDP per capita (GDPPC) and GDP per household (GDPHSH). The evolu-

23 SSP 2 - Middle of the Road (or Dynamics as Usual, or Current Trends Continue, or Continuation, or Muddling Through): In this world, trends typical of recent decades continue, with some progress towards achieving development goals, reductions in resource and energy intensity at historic rates, and slowly decreasing fossil fuel dependency. Per-capita income levels grow at a medium pace on the global average, with slowly converging income levels between developing and industrialised countries (Riahi et al., 2017).

24 Figures of population and GDP were downloaded from the IIASA SSP Database(Riahi et al., 2017).

Figure 3.21: Shared socio-economic pathways (SSP) 2020-2050 for GDP and population in Ecuador



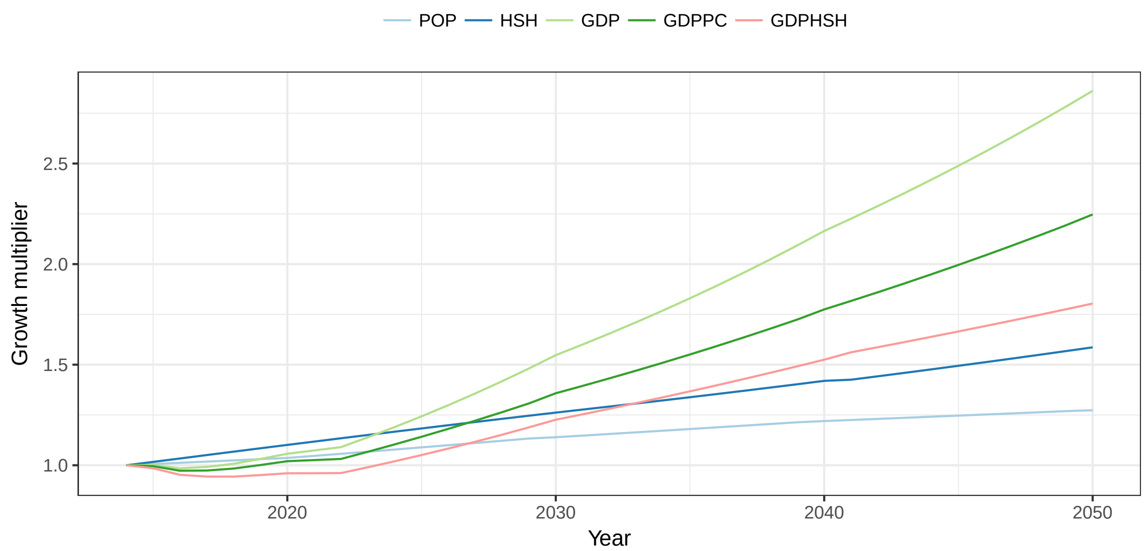
Source: Riahi et al. (2017)

Table 3.12: Socio-economic demand drivers for TIMES-Ecuador based on the Shared Socioeconomic Pathway SSP2

Year	GDP_{PPP}		Population	
	Billion $US\$_{2005}$	Annual growth rate (%)	Inhabitants (10^6)	Annual growth rate (%)
2017	127.7	0.7	16.7	0.7
2018	129.8	1.6	17.0	1.3
2020	136.3	2.4	17.5	1.3
2030	197.3	4.5	19.2	1.0
2040	264.6	3.4	20.6	0.7
2050	339.5	2.8	21.5	0.4
Average		2.7		0.67

Source: Riahi et al. (2017)

Figure 3.22: Socio-economic drivers growth projection



tion of these drivers according to the selected SSP2 scenario can be seen in Figure 3.22 on the previous page.

Drivers are linked to the end-use energy demands by a constant and sensitivity parameter. These sensitivities of demands are intended to reflect changing patterns in energy service demands in relation to socio-economic growth, such as saturation in some energy end-use demands, increased urbanisation, or changes in consumption patterns once the basic needs are satisfied. The constant and sensitivity parameters have been exogenously introduced in the modelling based on the European TIMES model (ETM-UCL) (Solano and Pye, 2015) and the developing country regions depicted in the Global TIMES Integrated Assessment Model (TIAM-UCL) (Anandarajah et al., 2011), and can be found in Table B.1 on page 294 in Appendix B. Given that there exist no reliable data for the forecast of industrial production, commercial or agricultural GDP growth until 2050, these sensitivities have been used to show how different industries evolve in relation to GDP growth and how a shift in GDP composition towards the industrial and commercial (service) sector, so that agricultural will become less important until 2050. In a next step, the sectoral drivers have been calibrated in such a way that they yield a more service orientated economy.

3.2.7.2 *Demand modelling*

Energy demand in TIMES can be modelled with a bottom-up approach, based on long-term assumptions (drivers) regarding demographic evolution, economic development, technological advances, and lifestyle changes. It starts from a lower level of aggregation to project final energy or end-use energy demand by type and by sector, based on the assumptions adopted. The main advantage of TIMES is that it allows to optimise supply and demand simultaneously, iteratively adjusting the optimal mix of energy and technologies on both supply and demand side to reach a least-cost solution for the whole energy system. However, this can also be seen as a drawback, given that energy demand does not necessarily behave in a least-costly manner, i.e. energy consumers make their choices considering a broader set of drivers, beyond energy and technology prices (Gnann et al., 2018). In any case, TIMES can be used as a simulation model on the demand side emulating models that follow exogenously determined pathways for technology uptake according to national policies or international trends. Details on demand modelling can be found in Appendix B on page 293.

Demand technologies have been modelled in TIMES-EC to represent more than 20 energy service demands (cooking, lighting, water heating, industrial process steam, heavy freight transport, etc.) in five economic sectors (residential, commercial, industry, trans-

Table 3.13: Energy services demands and drivers in TIMES-EC

Demand sector	Sub-sectors	Energy service demands	Unit	Driver
Residential		Refrigeration	PJ	GDPHSH
		Lighting	PJ	GDPPC
		Water heating	PJ	GDPHSH
		Cooking	PJ	GDPHSH
		Other uses	PJ	GDPHSH
Industry	Food & beverage	Steam	PJ	GDP
	Minerals & non-metals	Machine drives	PJ	GDP
	Textile	Process heat	PJ	GDP
	Wood & paper	Other uses	PJ	GDP
	Chemicals, plastic & rubber		PJ	GDP
	Manufacturing & others		PJ	GDP
Commercial		Electrical appliances	PJ	GDPPC
		Other uses	PJ	GDPPC
Transport	Freight	Heavy freight[a]	Million vehicle-km	GDP
		Light freight[b]	Million vehicle-km	GDP
		Maritime domestic	PJ	GDP
	Passengers	Private commute[c]	Million vehicle-km	GDPPC
		Public commute[d]	Million vehicle-km	GDPHSH
		Aviation domestic	PJ	GDP
Agriculture, construction & others		Electrical appliances	PJ	GDP
		Other uses	PJ	GDP

Note: [a]Trucks and trailers >15ton, [b]Trucks < 15 ton, [c]Cars, jeeps and motorcycles, [d]Buses. GDP: Gross Domestic Product, GDPHSH: Household GDP, GDPPC: GDP per capita, POP: population.

port and others). A driver is allocated to each energy service demand to project demand for future years throughout the model horizon (2010 to 2050). Table 3.13 on the preceding page includes details of the demand sectors, services and socio-economic drivers.

For each energy service demand, a number of existing and new technologies are in competition to satisfy it. They are characterised by an efficiency, an annual utilisation factor, a lifetime, O&M costs, and 36 time slice share coefficients. Different technology parameters such as cost and efficiency can improve over the years with vintages. No future investment is allowed in the existing demand technologies. In the next paragraphs, details on the demand sectors are presented:

TRANSPORT The transportation sector is characterised by six energy-service demands. The sector considers road transport of passengers and freight, domestic maritime and domestic aviation. Passengers' road transport is further divided in cars (private vehicles, taxis and two-wheelers) and buses, while freight road transport can be heavy (>15 ton) or light weight (<15 ton). Domestic aviation and navigation are considered, without further analysis of alternative technologies. There is a wide range of fuels represented in the model to power road transport: natural gas, LPG, gasoline, diesel, electricity and bio-ethanol, while maritime runs on heavy fuel oil and aviation on kerosene. Considering that the transport sector is Ecuador's largest final energy consumer, fuel switching and the introduction of new transportation technologies are modelled, e.g. the introduction of ethanol fuel blends as well as hybrid and electric vehicles (IEA, 2016a; BNEF, 2017). The main transport sector technologies' assumptions are sourced from TIAM-UCL (Anandarajah et al., 2011) and can be found in Appendix B in Table B.2 on page 295.

INDUSTRY The industrial sector is characterised by four energy-services, each representing the total energy requirement for different industrial sub-sectors. These sub-sectors are: i) food and beverage, ii) minerals and non-metals, iii) textile, iv) wood and paper, v) chemicals, plastic and rubber, and vi) manufacturing and other industries. For each one of these industrial branches there are different technologies and fuels modelled for supplying the following energy service demands: i) steam, ii) process heat, iii) machine drive, and iv) other uses. The share of these energy services according to the production processes of each sub-sector has been detailed according to the statistics of INER (2015) and can be seen in Figure B.1 on page 293 in Appendix B. Industrial energy demands capture both the growth trend of existing industrial demands and the progressive introduction of a set of energy intensive 'strategic' industries by 2025, which are a key part of Ecuador's current future economic development strategy (MEER, 2017a,b) and will be further details in Section 3.2.10 on page 151.

residential The residential sector includes five energy-service demands : i) refrigeration, ii) lighting, iii) water heating, iv) cooking, and v) other uses (electric appliances and air conditioning). Residential energy service demand in the residential sector are mainly driven by GDP per household projected to 2050. Cooking is the largest consumer of energy in the residential sector (see Figure 3.6 on page 112), which currently mostly uses LPG. Electric cooking (induction cookstoves) and electric water heating technologies have been represented in the model as an alternative to switch away from LPG to electricity, coinciding with one of Ecuador's energy demand policies for the short term (explained further in Section 3.2.10 on page 151)

commercial The commercial sector includes only two energy service demands, these are: appliances (electric) and other uses (fuel powered). There is no final energy use information in Ecuador's energy balance to desegregate demands in the commercial sector any further.

agriculture, construction & others Other sector such as agriculture and construction have similar to the commercial sector only two service demand: appliances (electric) and other uses (fuel powered). There is no final energy use information in Ecuador's energy balance to desegregate demands in the agriculture, construction & others sector any further.

In line with the expected socio-economic development for Ecuador in the period 2017 to 2050 and the respective driver allocation for energy service demands in the studied economic sectors, projected energy service demand is presented in Figure 3.23. Transport and the industry sectors are the fastest growing sectors in terms of energy service demands. Industrial demands show that manufacturing will be the sector that grows the fastest, influenced by the deployment of "strategic" energy intensive industries (explained further in Section 3.2.10 on page 151 and detailed in Table Table 3.22 on page 157). These strategic industries are a discrete one-of-a-kind investment according to industry design; however an interpolation has been considered between 2020 and 2025 to consider an incremental entrance of these industrial demands into the system until reaching full production capacity in 2025. Food & beverage and mining & non-metal industries remain the second largest growing in the industrial sector. Transport demand is characterised by a growing demand for heavy freight, aviation, light freight and cars, which more than doubles by 2050. The residential sector is characterised by lighting and other (air conditioning) growth, while refrigeration and cooking grows slower due to lower population growth rates. The commercial sector shifts to electric powered energy services similar to the agriculture, construction & others sector.

3.2.7.3 *Electricity load profiles*

Power demand is not constant over the day or over the year in Ecuador. Hourly-records of power dispatched to the SNI by the Ecuadorian grid operator for year 2016 were assessed to determine changes in the load curve during the day and the individual demand load profiles of the residential, commercial and industrial sectors (CENACE, 2015). Figure 3.24 on page 146 shows the contribution of different energy consumption sectors to the average daily load curve registered for 2016. Notice that the residential and industrial sectors are the largest energy consumers. The prevalence of three clear distinct load patterns are visible throughout the day. The lowest demand is registered in the early morning from 00:00 to 8:00, followed by a mid-load during the day from 8:00 to 19:00, after which peak load kicks in between 19:00 and 00:00. Peak load in Ecuador was around 3,500 MW in 2016 and it occurred mostly between 19:30 and 20:00. This analysis has aided the daily time slice definition mentioned previously in the structure of TIMES-EC in Section 3.2.4 on page 119.

Figure 3.25 on page 146 shows average daily load profiles for months of the year in 2016. Seasonal variations of the daily load curve are small. This load profile evidences the lack of extreme weather in Ecuador, which reflects in low use of electric cooling and heating appliances. Despite the small changes that the daily load profile experiences according to the months of year, these change will be registered in TIMES-EC given that the model has a seasonal time slice resolution of 12 months, as mentioned in Section 3.2.4 on page 119.

3.2.8 *Transmission and distribution*

The Ecuadorian power system is characterised by a single transmission system – the SNI – as has already been mentioned previously in Section 3.2.2. Transmission lines that interconnect the country with Colombia and Peru are also represented in TIMES-EC, although current interconnection capacity is limited (525 MW with Colombia and 110 MW with Peru). Ecuador is permanently interconnected with Colombia and in cases of emergencies it can interconnect with Peru (SINEA, 2015). At the moment of writing, no new inter-connectors are being considered, therefore the possible future expansion

Figure 3.23: Projected energy-service demands in Ecuador

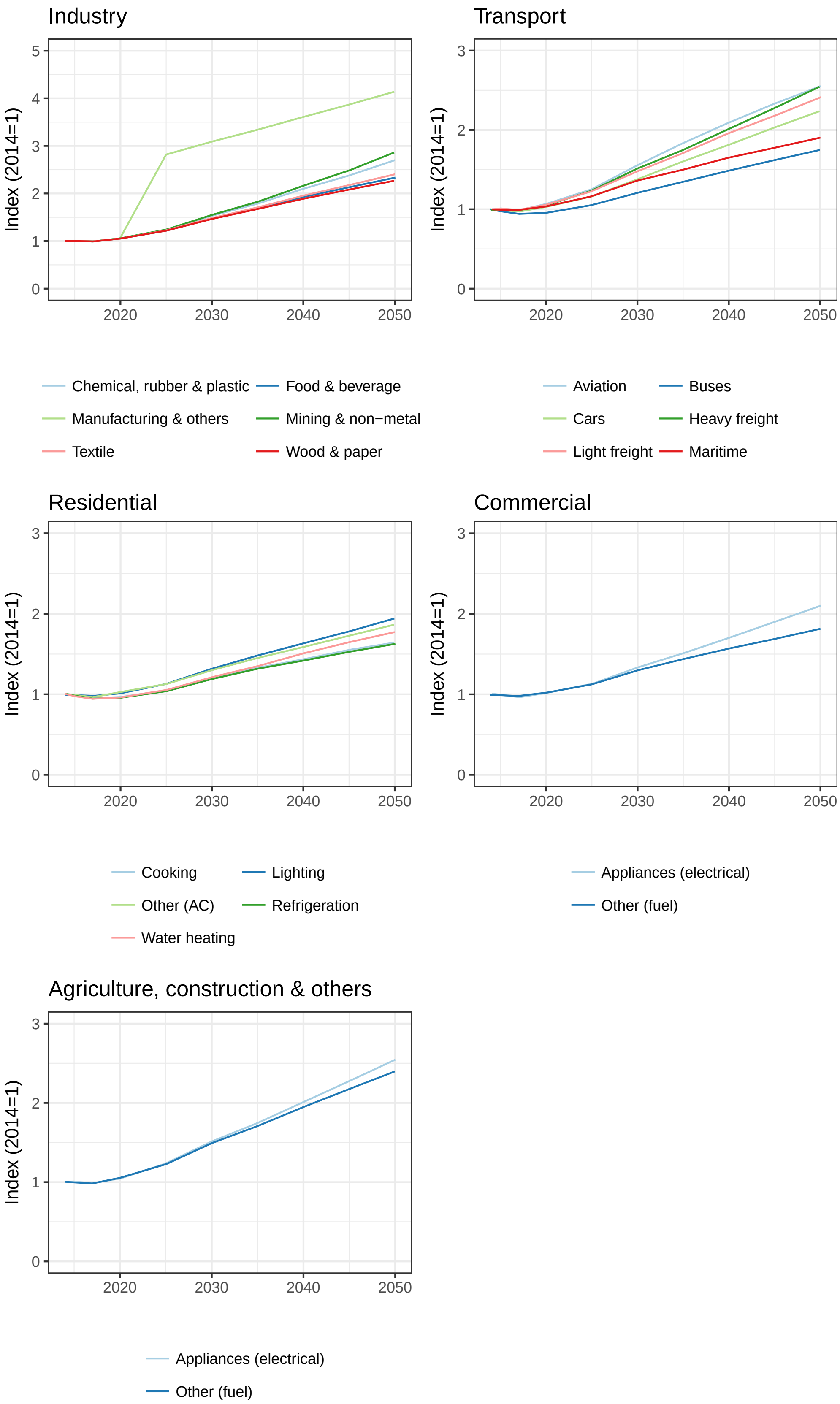


Figure 3.24: Daily load profile disaggregated by consumption sectors for Ecuador in 2016

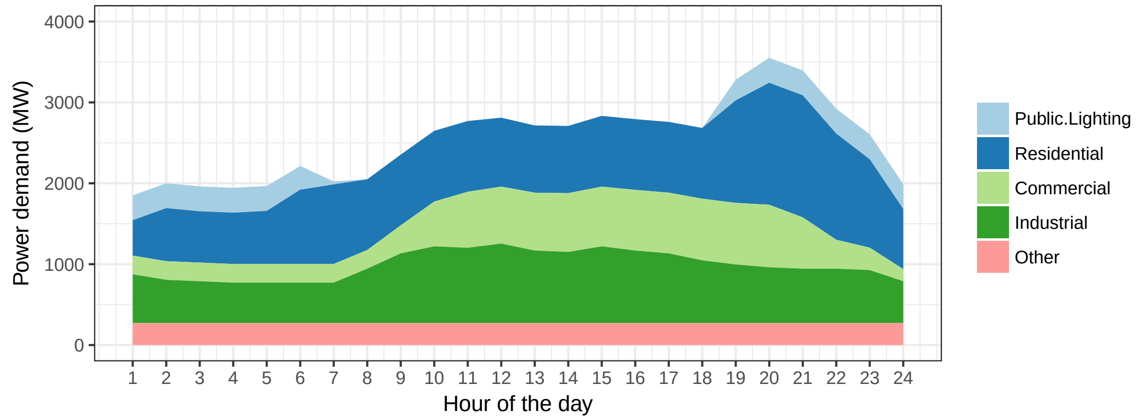
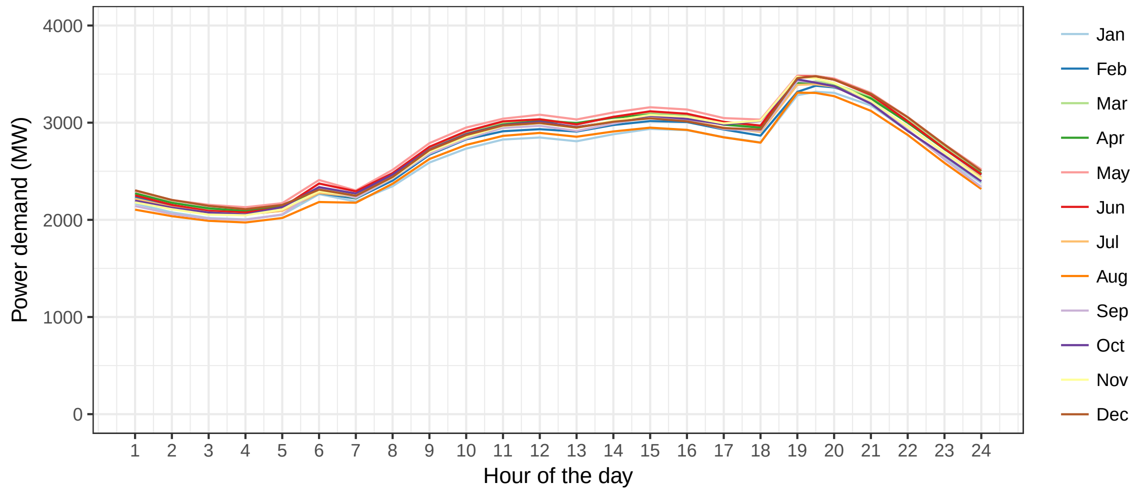


Figure 3.25: Daily load profiles averaged for months in Ecuador for 2016



of these links is not considered in this particular analysis. Traditionally, power has been transmitted between Ecuador and Colombia, thus offering balancing services between seasons with low and high prices. However, since Ecuador commissioned its large hydropower infrastructure in 2016, imports from Colombia have dropped drastically and exports our now on the rise.

In TIMES-EC the national low-voltage distribution grid has not been described with particular detail. In the model the power transmission and distribution grids have been taken into account by describing the losses, which imply that the power plants in stock must produce more power than just the electricity demand, because a part of the production is lost during transmission. Transmission and distribution losses between power plants and final consumers have been aggregated and represent a fraction of electricity generated that decreases from 12% in 2017 to 10% in 2050, in line with Ecuadorian projections for grid improvements (MEER, 2017a).

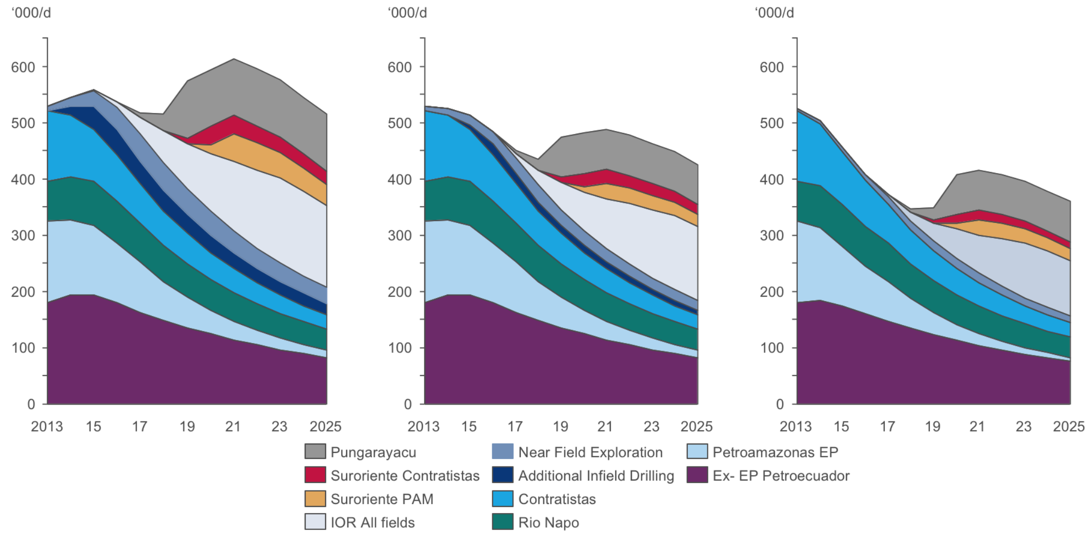
3.2.9 *Energy resources, prices and conversion technologies costs*

The supply commodities described in TIMES-EC are: crude oil, natural gas, biomass, municipal solid waste, firewood, wind, solar, geothermal, water and electricity.

Ecuador is a net energy exporter. Crude oil is the main energy export (~400 thousand barrels per day in 2017) (OPEC, 2017). However, only limited refining capacity is available in the country and a diversity of petroleum products must be imported (Chavez-rodriguez et al., 2018). TIMES-EC considers crude oil and natural gas as domestic primary energy sources. Table 3.14 on page 150 summarises petroleum and gas statistics for Ecuador in 2017 according to OPEC (2017). Petroleum products considered in TIMES-EC are diesel, kerosene, liquified petroleum gas, gasoline, residual fuel oil and heavy fuel oil. The processes that make fossil fuel commodities available are only of two kinds: import technologies ("IMP") and extraction technologies ("MIN"). The proper supply processes have been associated to each commodity in accordance to the Ecuadorian Energy Balance 2015 (MICSE, 2015). Crude oil and natural gas is extracted (until reserve depletion, after which imports begin), petroleum products can be refined or imported. Moreover, for every commodity there is the possibility to add constraints regarding the maximum extraction and maximum import per year. Ecuador's refinery park has also been represented with a capacity of 190.8 thousand barrels per day.

The energy prices of principal energy sources are presented in Table 3.16 on page 150. Fossil fuel prices are represented individually for a range of petroleum products, capturing the distinction between crude oil and other grades. The projected oil and natural

Figure 3.26: Oil production profile in Ecuador for high (left), middle and low (right) investment scenarios, and current and expected oil fields



Source: MRNNR (2013)

gas prices employed in the model are based on the U.S. Department of Energy Annual Energy Outlook 2017 with projections to 2040 (EIA, 2017), which considers long-term prices for oil to be 110 US$ per barrel and for natural gas 5 US$ per million Btu. This long-term price trend obeys to the Reference scenario of EIA projections, which is a middle-of-the-road price assumption for crude oil and natural gas (see Figure 2.7 on page 85 for other EIA crude oil and natural gas scenarios). The range of prices in 2040 for crude oil is betwen 50 - 225 US$ per barrel and 3.5 - 10 US$ per million Btu. It is mentioned that projecting future oil an gas prices is difficult and no agency in general has been able to project prices successfully (see retrospective analysis report EIA (2018a)). Using deterministic projections of fossil fuel prices (be them high, low or middle-of-the-road) will be challenged in following Section 3.3 on page 159 and will be treated with a the probabilistic approach integrated into TIMES-EC. Gas prices are still regional, as they require significant infrastructure for import/export, therefore we have added the capital cost for floating and on-shore regasification units to 150 and 200 US$/ton, respectively, according to IGU (2017). In the years beyond those for which the cost is given, the costs are calculated with linear extrapolation. It is assumed that the price difference between crude oil and oil products will be constant from 2017 to 2050.

Domestic supply of oil has been modelled with the projected supply curve for the mid-investment production scenario until 2025 from the Plan of Hydrocarbons of the Ministry of Non-renewable energy resources (MRNNR, 2013). The production level until 2050 has been extrapolated to reach a level of 200 thousand barrels per day. Figure 3.26 shows oil production scenarios in Ecuador up to 2025 for three levels of investment, notice that all scenarios have decaying production curves, which shows the maturity of

Ecuadorian oil fields and not a very bright future in terms of increaesd production or reserves. Domestic oil production cost is shown in Table 3.15 on the next page. Export oil price is slightly under the price of oil imports, to ensure that the model first produces domestic oil before importing. Regarding gas production, given the small reserves and that most comes from one field in the Guayaquil Gulf coast, it has been assumed a constant gas production value of what has been shown in Table 3.14 on the following page and a production cost of 5.3 USD per million BTU (5.02 million USD per PJ) in 2013 (MRNNR, 2013) and thereafter a cost slightly lower that the projected import price of gas. The electricity import price, representing power sent by interconnections from Colombia and Peru is exogenously given to the TIMES-EC model and is expected to have an annual increase of 0.8% from 2017, according to historic data (ARCONEL, 2016). There are no upper limits on import of energy. Conventional energy carriers, namely oil and natural gas are included in the model with their corresponding CO_2 emissions.

The representation of Ecuadorian renewable energy potentials (hydropower, wind, solar, geothermal and biomass) is based on national studies for current and future technologies. Table 3.17 on page 151 presents a summary of renewable energy potential in Ecuador. Solar energy is abundant in Ecuador, given the country's location on the geographical Equator. The Ecuadorian Solar Atlas (CONELEC, 2008) estimated an annual average solar potential of 4.6 $kWh/m^2/day$. In contrast to solar energy, wind energy potential is limited. Due to Ecuador's location in the tropics at the most Western part of South America, trade winds are the prevailing pattern of easterly surface winds that are available after crossing the entire continent. This causes great scale horizontal winds to be rather weak in most parts of the country and therefore wind energy potential from onshore wind facilities to be small (MEER, 2013). The Ecuadorian Wind Atlas (MEER, 2013) shows sites with annual average wind speeds between 6 to 8.5 m/s and a cumulative capacity of 1,600 MW for the long term. Regarding geothermal techno-economic energy potential, the country has identified a handful of prospective projects summing up a total of 900 MW. There is no geothermal capacity currently installed at the time of writing but the first exploration wells were drilled in 2017 (MEER, 2017a).

Technical bioenergy potential, which includes agriculture residues, livestock and forestry resources could be equivalent to 177 PJ/y according to the Ecuadorian Bioenergy Atlas (MEER, 2014). However, as the distribution chains and technology to use this resource in Ecuador is still incipient, the Electricity Master Plan (PME) considers that the maximum power generation from biomass could be 12.7 TWh/y by the year 2025 (equivalent to a firm capacity of 500 MW) (MEER, 2017a). The supply cost of biomass and municipal solid waste has been set to 2 million US$ per PJ in 2015, reaching 4 million US$ per PJ

Table 3.14: Petroleum and gas statistics for Ecuador in 2017

Fossil fuel statistic	Unit	Value
Crude oil		
Proven crude oil reserves	million barrels	8,273
Crude oil production	1,000 barrels per day	549.0
Refinery capacity	1,000 barrels per day	190.8
Oil demand	1,000 barrels per day	247.0
Crude oil exports	1,000 barrels per day	414.7
Exports of petroleum products	1,000 barrels per day	31.4
Natural gas		
Proven natural gas reserves	billion m^3	10.9
Marketed production of natural gas	million m^3 per day	530.0
Natural gas exports	million m^3	-

Source: OPEC (2017)

Table 3.15: Domestic oil supply and cost curve

	Proven crude oil reserves		Cost
	(million barrels)	(PJ)	(million USD per PJ)
Step 1	5,836	35,700	3.8
Step 2	1,455	8,900	5.2
Step 3	982	1,000	7.0
Total	8,273	50,600	

Source: MRNNR (2013)

Table 3.16: Energy price assumptions for 2017, 2020 and 2050

Energy source	Unit	2017	2020	2050
Primary energy				
Crude oil	US$/barrel	44	47	110
Natural gas	US$/MBtu	3	3.2	5
Petroleum products				
Heavy Fuel Oil	US$/barrel	75	80	168
Diesel	US$/barrel	66	71	148
Gasoline	US$/barrel	64	69	144
LPG	US$/barrel	25	26	55
Electricity				
Import from Colombia/Peru	US$/MWh	153	155	208

Source: EIA (2017)

Table 3.17: Ecuadorian renewable energy potential for electricity expansion

Source	Unit	Potential
Hydropower[a]	MW	13,002
Wind[b]	MW	1,600
Solar[c]	$kWh/m^2/day$	4.6
Biomass[d]	PJ/y	177
Geothermal[e]	MW	900

Source: [a]ARCONEL (2015), [b]MEER (2013), [c]CONELEC (2008), [d]MEER (2014) , [e]ARCONEL (2015)

in 2050 according to the Ecuadorian Bioenergy Atlas (MEER, 2014). The cost associated to the mining process of water, solar, geothermal and wind has been set equal to zero.

3.2.10 *Scenarios: policy and climate change*

3.2.10.1 *Energy policy overview*

During the last decade, Ecuador's main energy policy has been to attain a power generation matrix with a 90% share of renewable energy by 2021 (SENPLADES, 2009; MEER, 2017a; SENPLADES, 2017). The policy has been centred around the development of large capacity hydropower infrastructure led by the central government (Zambrano-Barragen, 2012). Recent additions of hydropower have enabled the share of hydropower electricity generation in the national grid to reach over 82% in 2017, while the share of other renewable energy sources remains low at 2.7% (see Table 3.6 on page 114). At present, Ecuador is close to achieving its renewable energy targets for the overall power matrix. Despite these achievements, the Electricity Master Plan (PME) (MEER, 2017a) details plans for an envisioned capacity expansion portfolio for the period 2016-2025 that could add a further 2 – 3.5 GW of hydropower capacity in the mid-term.

Regarding long-term energy policy, the National Energy Agenda 2016-2040 sets an explicit policy to – *"continue harnessing hydropower and sustain a predominantly hydro-based power system"* (MICSE, 2016a). The reliability and cost of electricity supply is viewed as a critical factor for Ecuadorian economic development. The 'Transformation of the Productive Matrix' initiative is a set of national industrial policies which seek to transition Ecuador away from primary resource dependence (namely crude oil exports) towards an industrial and knowledge-based economic model that produces exports with higher added value (SENPLADES, 2012; Purcell et al., 2017). Within this strategy, one of the main activity areas is the development of strategic energy-intensive industries such as oil refineries, petrochemicals, aluminium, copper and steel industries that are planned to be deployed between 2016-2025 (MCPEC, 2016), and which explicitly rely on the constant deployment of large hydropower infrastructure (details of these strategic industries are found in Table 3.22 on page 157).

Regarding the decarbonisation of the energy sector, Ecuador is a signatory to the United Nations Framework Convention on Climate Change (UNFCCC) and forms part of the Non-Annex I group of countries, and hence has voluntary commitments for GHG mitigation actions. The Ecuadorian government has demonstrated an awareness of the adverse effects of climate change on human and ecological systems and a willingness to strictly adhere to international agreements. Accordingly, Ecuador has formulated a variety of climate mitigation and adaptation policies, including the submission of an intended NDC as part of the COP21 process (UNFCCC, 2015b). At the heart of the Ecuadorian NDC is the inclusion of plans to expand hydroelectric capacity by between 2.8 – 4.3 GW by 2025, which includes the latest capacity additions and more. Further decarbonisation efforts are stated in the the National Plan for Energy Efficiency 2016-2035 (PLANEE) (MEER, 2017b), which focuses on three main policies: i) the replacement of inefficient appliances (refrigerators mainly) and switching cooking from subsidised LPG to electricity in the residential sector; ii) implementing energy efficiency standards in the industrial sector (ISO 50.001); and, iii) switching to efficient public lighting, by using LED technology (Chavez-rodriguez et al., 2018).

Hydropower is therefore currently considered as the main means of attaining energy security in Ecuador, reducing electricity prices, mitigating GHG emissions and forming the backbone for the above-mentioned industrial and economic development strategy. However, as noted in the Introduction on page 3 and in the Literature review on page 23, anthropogenic warming may substantially affect critical hydroclimatic variables that might alter hydropower generation and impact those objectives. In addition, the upscale of large hydropower might have other issues for its deployment in terms of environmental and social challenges (Anderson et al., 2018) and the inherit complication of large-scale infrastructure projects (Callegari et al., 2018).

3.2.10.2 *Hydropower development scenarios*

A range of three policy cases focusing on hydropower supply have been developed separately from the future climate change scenarios detailed in Section 3.2.5.4 on page 133. It is emphasised that the policy cases and climate developments are two different types of model input. While the climate assumptions explore the long-term uncertainty of hydropower production under uncertain future hydroclimatic conditions, the policy cases

Table 3.18: Overview of policy cases relevant for hydropower development

Policy case	Description
Boost Hydropower	Boost the expansion of hydropower according to Government plans up to 2025.
Constrain Hydropower	Constrain the investment in large hydropower, only medium and small hydropower.
Environment Priority	Prioritise emission cap according to the Government NDC and no large hydropower.

explore different long-term evolutionary pathways for the energy system as the result of various energy and environmental policy decisions. It is noted that all scenarios consider government policies to some extent and therefore none of them gives a fully cost optimised suggestion on how to invest in hydropower. Table 3.18 summarises the policy cases that will be addressed in combination with the climate change scenario analysis.

boost hydropower The first policy case, represents a continuation of Ecuador's current national hydropower-led energy policy as set out by the PME (MEER, 2017a) and in Ecuador's NDC to the Paris Agreement up to the year 2025 (UNFCCC, 2015b). This policy case considers that two new large hydropower projects located in the Santiago basin start operation within the period of analysis: i) Paute-Cardenillo (595.6 MW) by 2023 (CELEC, 2018a) and ii) Santiago-G8 phases 1–4 (2,400 MW) by 2025 (CELEC, 2017). At the time of writing, both projects have now completed their final design studies and are considered key to supplying the demand for electricity in future strategic industries. In addition to hydropower, the PME mentions plans for future developments in natural gas (187 MW), geothermal power (150 MW), small hydropower (140 MW) and a batch of wind and small utility scale PV (200 MW). Details for technologies and capacities deployed in this scenario can be found in Table 3.19 on the following page. Therefore, this scenario forces investment of 3.15 GW of new hydropower between year 2018 and 2025, simulating that the expected NDC-oriented expansion plan is accomplished. Beyond 2025, no hydropower or any other technology is forced into the system and therefore the system gives a cost optimised suggestion on how to develop the power system from 2025 until 2050. This scenario was chosen because Ecuador, although defining an intended NDC focused on hydropower, has not expressed the expected reductions that this deployment of hydropower would achieve. This scenario will seek to quantify the power sectors-related emissions with this large deployment of hydropower, as to have a reference scenario of current policies.

Table 3.19: Capacity additions for the 'Boost Hydropower' policy case between 2016-2025

Type	Capacity (MW)	Basin	Current state	Expected entry year
OCGT*	77	-	Under construction	2018
ROR*	4	Santiago	Under construction	2018
ROR*	10	Esmeraldas	Under construction	2018
CCGT*	110	-	Under construction	2018
Wind, PV*	200	-	Legalising permits	2022
DAM*	595.5	Santiago	Final design	2023
ROR**	140	-	Study phase	2023
Geothermal**	150	-	Study phase	2023
DAM**	2,400	Santiago	Final design	2023-2025
Total	3,686			

Note: *Projects to supply natural demand growth, **Additional projects to supply strategic industries
Source: MEER (2017a)

CONSTRAIN HYDROPOWER The second policy case, assumes the cancellation of planned large hydropower projects (>450MW). Total future hydropower potential is assumed to be reduced from 13 GW down to 3.2 GW (see Section 3.2.5). Current large hydropower plants continue operating, and investments in small and medium sized hydropower projects remain as expansion options. This policy case reflects concerns that large hydroelectric deployment in basins such as the Amazon, the Congo, and the Mekong, have the potential to cause serious environmental and social impacts (Schaeffer et al., 2013; Tundisi et al., 2014; Fearnside, 2015; Winemiller et al., 2016; Gracey and Verones, 2016; Latrubesse et al., 2017). Accordingly, there is the possibility that these projects may experience severe delays, cost overruns and possible reductions of the originally envisaged production capacity (Ansar et al., 2014; Sovacool et al., 2014c). The most recent hydropower station in Ecuador, Coca Codo Sinclair (1.5 GW), though currently the largest in terms of its installed capacity, has itself been constructed with only a small storage reservoir due to environmental concerns in a sensitive area for biodiversity in the Amazon (Escribano, 2013). The large hydropower projects that would be left out of in this scenario are detailed in Table 3.20 on the next page and are six: Santiago G8 (3.6 GW), Santiago G9 and G10 (3.18 GW), Verdeyacu Chico (1.17 GW), Catacahi (0.74 GW), Paute Cardenillo (0.59 GW) and Chespi-Palma real (0.46 GW). The complete list of projects can be found in Table A.1 on page 289 in the Appendix.

Table 3.20: Remaining hydropower potential in Ecuador by potential and number of projects.

Basin	Large (>450 MW)		Medium (50 - 450 MW)		Small (1-50 MW)		Total	
	MW	No.	MW	No.	MW	No.	MW	No.
Esmeraldas	460	1	1164	10	581	24	2205	35
Guayas					14	5	14	5
Jubones					70	9	70	9
Santiago	7376	3	525	5	76	3	7978	11
Pastaza			368	2	34	3	402	5
Napo	1920	2	270	1	143	5	2333	8
Total	9756	6	2327	18	918	49	13002	73

Source: ARCONEL (2015)

ENVIRONMENT PRIORITY The third policy case, is used to explore how Ecuador might achieve the GHG reduction targets implied by the Ecuadorian NDC (UNFCCC, 2015b) but without the use of any additional large hydropower projects. The policy case assumes that the emission levels that are expected to be attained through large hydropower deployment in the Boost Hydropower policy case (which is aligned with Ecuador's NDC) must be achieved, but additionally constrains the deployment of large hydropower infrastructure in a similar fashion to the Constrain Hydropower policy case. The motivation behind this policy case assumption is to explore the possibility of maintaining low emissions without the environmental and social risks to project delivery associated with large hydropower projects (Anderson et al., 2018).

3.2.10.3 *Demand side scenarios*

A single energy demand scenario has been considered in TIMES-EC based on the demand drivers and energy services detailed in Section 3.2.7 on page 138. It is assumed that energy efficiency measures stated in the PLANEE energy efficiency plan (MEER, 2017b) will be successfully implemented by 2035, after which no improvements are promoted. Table 3.21 on the following page presents the demand side policies and efficiency improvements that have been considered for the period 2007-2035 as stated in the PLANEE. Technologies for transport have been forced to at least reach the minimum levels suggested in the PLANEE. Similarly, the residential sector is forced so electric cooking and water heating replaces LPG-fired units, by at least what the PLANEE states. For industry, appliances with better efficiency according to the values stated in the PLANEE will be available for the model to choose from.

Table 3.21: Demand side policies and estimated energy demand reductions for Ecuador according to the PLANEE up to 2035

Demand sectors	Policy description
Residential and Commercial	Improvement in 10% of energy efficiency by replacing appliances: substitution of LPG cookers by electrical induction cookers in 80% of households by 2050, reduction of cooking with firewood to 1% on households by 2050, substitution LPG boilers by electrical showers in 80% of households by 2050.
Transport	Substituting 10% of cars with public transport (buses)
	Reducing 5% of energy intensity through vehicle labelling.
	Scraping 2,000 vehicles per year and renewing car fleet.
	Introducing biofuel blends: 5% ethanol blend (E5) for cars and biodiesel (B5).
	Introducing 15% of electric cars and 15% of electric light freight vehicles by 2050.
Industrial	Implementing cogeneration technologies. Improvement energy efficiency in 10%.
	Replacing old motors, pumps, boilers and heaters. Improvement energy intensity in 10%.
Total cumulative reduction between 2007-2035	

Source: Chavez-rodriguez et al. (2018); MEER (2017b)

Table 3.22: Strategic industries' energy demand in 2025

Industry	Description	Power (MW)	Electricity (GWh/y)	Gas (mill. m^3/y)	Oil (bpd)
Aluminium	Foundry of primary aluminium – 560 kton/y	858	7,953	28	-
Copper	Foundry and refining of copper concentrate – 280 kton/y	62	429	61	895
Steel	Production of Hot Rolled Coil and Cold Rolled Coil (CRC) Steel	24	57	350	-
Petrochemicals	Production of Linear Alkylbenzene and Polyethylene terephthalate	20	120	-	3000
Refinery	Heavy crude oil refinery for motor gasoline and diesel – 200 kbpd	300	2,234	-	200 k
Mining & Others	Gold and copper mining projects	469	2,756	-	-
Total		1,733	13,549	439	204 k

Source: MCPEC (2016); MEER (2017a)

To represent industrial policy, the introduction of a set of energy intensive industries has been modelled according to Ecuador's Industrial Policy 2016-2025 (MCPEC, 2016) in addition to current existing industrial demand (see Section 3.2.7 on page 138). Table 3.22 summarises the energy demand characteristics of these 'strategic industries' (aluminium, copper, steel and petrochemicals), a new heavy crude oil refinery and various mining projects (MEER, 2017a). By 2025 these industries are expected to require 1,733 MW of firm capacity and 13,549 GWh of electricity, which represent a significant increase compared to current installed capacity and electricity demand. Only he aggregated values of final energy demand by source for these industries are considered, given the lack of information available regarding the processes and machinery that they would require.

The integration of demand side policies with drivers, sensitivities and socio-economic projections lead to a scenario for each of the detailed energy demand or energy service demands for the period 2017-2050. The projected energy service demands can be found in the following chapter in Section 4.2.3 on page 212.

Table 3.23: Conceptual framework for integrated scenario analysis.

		No climate change (Historic)	Climate futures		
		NoCC	Dry	Mean	Wet
Policy case	Boost Hydropower				
	Constrain Hydropower	Baseline	Core future scenarios		
	Environment priority				

3.2.10.4 *Integrated scenarios: policy and climate change*

The most important inputs for TIMES-EC are a set of integrated scenarios which are characterised by the elements or dimensions of uncertainty that they incorporate. In the integrated scenarios there are two key dimensions of uncertainty to consider. The first is uncertainty of climate change and how patterns of precipitation could change in the future within the country, as discussed in Section 4.1.2 on page 189. Different GCMs present different views on how climate in the country may evolve, and this will in turn affect hydropower availability. The second dimension of uncertainty is the trajectory of energy policy development in regards to hydropower capacity expansion, which not only includes restrictions on large-scale hydropower development in the Amazon, but also the level at which Ecuador complies with its NDC.

Table 3.23 presents the conceptual framework for this scenario analysis and shows how each scenario combines hydropower development policy and climate futures. To focus on the impact of different climates, the results from the scenarios using future climates (Wet, Dry and Mean) should be compared to a modelled "baseline" or no climate change scenario (NoCC) – in other words, the hydropower generation, system costs and GHG emissions that we would expect if the climate from 2014 to 2050 was similar to the historical climate.

The rationale for exploring the integration of these scenarios is related to the policy questions for decisions-makers in the region. For example, from the point of view of the Government, the question is: *"How will our current expansion plans be affected by changing climate and potential restriction conditions?"* This is tackled by the Boost Hydropower and Constrain Hydropower scenarios. However, from a global perspective there is the pressing question of: *"What is the necessary power generation portfolio to meet NDCs while complying with other standards of sustainability?"*. This is tackled by the Environment priority scenario, which caps emissions but also large-hydro power expansion in environmentally sensible regions.

3.3 INTEGRATING PORTFOLIO THEORY INTO TIMES-EC

Energy system optimisation models are used to inform energy planners in the design of reliable, secure and least-cost power system investment portfolios. These tools usually rely on deterministic assumptions about future factors such as technology costs and fuel prices, which are uncertain but at the same time crucial parameters for the least-cost optimisation process. Expanded methodologies to assess uncertainties in energy models usually include the application of sensitivity and/or scenario analyses of a small number of generation portfolios (Decarolis et al., 2017), as was discussed in Section 2.3.2 on page 72. Despite the value of these methods in exploring future uncertainty, there remain inherent limitations in their ability to appropriately account for recurring[25] and interacting uncertainties over important parameters, such as capital cost of electricity infrastructure and fossil fuel prices (Awerbuch and Berger, 2003). As such, they do not provide a detailed analysis of the future risks associated with particular portfolio choices (Vithayasrichareon et al., 2014) or the options to hedge from risk (Parkinson and Djilali, 2015).

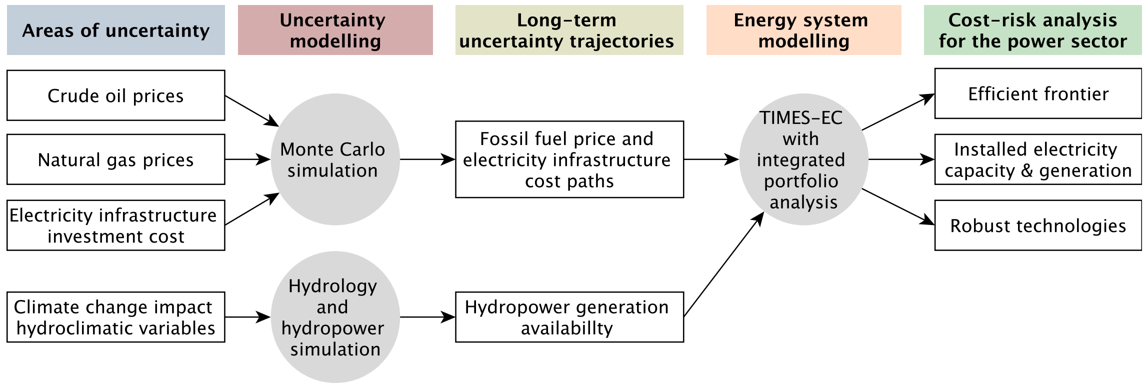
The purpose of this section is to present a novel method to integrate a financial Portfolio Theory analysis module into the TIMES-EC model. In developing this type of analysis, it is hoped that it sheds light on the impact that the uncertainty and volatility of fossil fuel prices and cost overruns can have on the long-term least-cost power system development pathway. By improving the inclusion of uncertainty in an energy system model, the energy planning process benefits, as more realistic estimates avoid financial losses and a better evaluation of investment portfolio alternatives.

A graphical description of the method used is shown in Figure 3.27 on the next page. To characterise the uncertainty of key input prices and costs, Monte Carlo simulations that consider probability distributions are used to create long-term evolution trajectories of the price of crude oil, natural gas and the cost of electricity generation infrastructure. Climate change uncertainty is assessed separately through scenarios which provides inputs of hydropower availability, as was presented in Section 3.2.10 on page 151.

Outputs from TIMES-EC with an integrated portfolio analysis module will consist of a series of energy portfolio investment scenarios by 2050 with different technology configurations. In addition, the cost-risk trade-off among different generation technology portfolios and identification of robust electricity generation technologies can also be assessed.

25 Recurring uncertainty is characterised by conditions that are periodically recurring and in which knowing the past or current value of the parameter does not resolve the uncertainty for the future.

Figure 3.27: Method applied in this study to assess uncertainty of future least-cost generation portfolios for Ecuador.



3.3.1 *Mean-variance portfolio theory in TIMES-EC*

The key feature of portfolio-based electricity generation investment analysis is that the value of each generation technology option should be determined in the context of particular overall generation portfolios (Roques et al., 2006). The assessment focuses on the impact that adding or removing particular generation technologies can have on the cost and risk of the overall generation portfolio. Typically, with this approach, each generation technology is evaluated on the basis of its contribution to overall portfolio generation costs and cost risk, rather than on the basis of stand-alone cost. The cost risk under the standard *Mean-Variance* Portfolio Theory (MVPT) analysis is represented by a standard deviation[26] of generation cost, implying the spread of possible portfolio costs (Awerbuch and Berger, 2003).

In MVPT, the expected cost of the electricity portfolio cost is calculated from the weighted average of the individual technology costs in the portfolio while the expected risk is determined from a weighted average of risks of the individual technology based on their correlations and covariances (Vithayasrichareon, 2012). Expected cost and risk

26 In statistics, the standard deviation (SD) is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values. The standard deviation of a random variable, statistical population, data set, or probability distribution is the square root of its variance. A useful property of the standard deviation is that, unlike the variance, it is expressed in the same units as the data.

of electricity generation portfolios under the MVPT are calculated from Equation 3.18 and Equation 3.19, respectively:

$$E\left(C_p\right) = \sum_{i=1}^{N} X_i E\left(C_i\right) \tag{3.18}$$

$$\sigma_p = \sqrt{\sum_{i=1}^{N} X_i^2 \sigma_i^2 + \sum_{i=1}^{N} \sum_{j=1}^{N} X_i X_j \rho_{ij} \sigma_i \sigma_j} \tag{3.19}$$

where, $E\left(C_p\right)$ is the expected generation portfolio cost, $E\left(C_i\right)$ and X_i are the expected levelised generation cost ($/kWh) and the share of technology i in the portfolio, σ_p is the expected portfolio risk, σ_i is the standard deviation of the cost of electricity from technology i, and ρ_{ij} is the correlation coefficient between cost of technology i and j. Notice that this approach, as presented here, relies on the LCOE of a particular technology, which does not consider system integration costs. In reality, the average value of unit of electricity that can be produced with intermittent solar photovoltaic, for example, would not have the same value than a unit produced with dispatchable power plants, given that intermittent technology require investments in the rest of the system to operate (e.g. storage, flexible backup capacity, reinforced transmission, etc.). However, given the low share of intermittent renewable energy that will be observed in the results, it is assumed that the system can absorb these shares without incurring in additional system integration costs.

In a deterministic energy system optimisation model, the minimisation of system cost with a constrained level of risk could be expressed as follows in Equation 3.20 (similar to Equation 3.13 on page 117 in Section 3.2.3.2):

$$\min E\left(C_p\right) = \min \sum_{i=1}^{N} X_i E\left(C_i\right) \tag{3.20}$$
$$s.t. \quad \sigma_p \leq R$$

where, R represents a predefined maximal level of accepted risk. Note that the notation $E\left(C_i\right)$ is used here as the cost resulting from the investment and operational decisions when the expected value of each uncertain parameter is used to compute the cost. By varying this maximal level of risk, a trade-off between the expected cost $E\left(C_p\right)$ and the associated risk of a portfolio σ_p can be made. A so-called 'efficient frontier' can be created by varying the risk between the risk of the 'minimal risk portfolio' and the 'minimal cost portfolio'.

A commonly used alternative formulation for MVPT includes the risk component directly into the objective function, as can be seen in Equation 3.21:

$$\min \left(E\left(C_p\right) + \alpha \times \sigma_p\right) \tag{3.21}$$

where, α is a parameter representing the attitude of the stakeholder towards risk.

There is an important consequence of this mathematical formulation. For risk neutral stakeholders ($\alpha = 0$), the solution of the portfolio-theory model that includes uncertainties is identical to the solution of a deterministic risk-neutral model (see Equation 3.20).

Nijs and Poncelet (2016) indicate that the use of the standard deviation as a measure for the cost of uncertainty (risk) requires a nonlinear, non-convex model to compute a final solution, which imposes a computational restriction on the linear optimisation framework of TIMES. Therefore, Loulou and Lehtila (2016) propose to replace the standard deviation by the so-called 'Upper Absolute Deviation' (UpAbsDev). It follows that the objective function of the energy system optimisation model then becomes:

$$\min \left(E\left(C_p\right) + \gamma \times UpAbsDev\left(C_p\right)\right) \tag{3.22}$$

$$UpAbsDev\left(C_p\right) = \sum_{i=1,j=1}^{N} \left(p_j \times \left\{C_i - E\left(C_i\right)\right\}^+\right) \tag{3.23}$$

where the objective function takes into account risk by including the level of risk aversion parameter γ and the risk measure $UpAbsDev$. The risk aversion parameter γ can be represented as a variable cost on the flow of $UpAbsDev$ and its variation allows to find the efficient portfolios (similar to the R constraint in Equation 3.20). The $UpAbsDev$ computes the average value of the positive total cost deviations $\left\{C_i - E\left(C_i\right)\right\}^+$ for all states-of-the-world j (with probability p_j).[27]

This detailed mathematical formulation can be implemented in TIMES in two steps:

1. Replacing the standard deviation with the 'Upper Absolute Deviation' (UpAbsDev) and calculating its value for energy commodities price and electricity generation technologies cost deviations for the modelling horizon.

2. Creating a series of dummy flows to represent the financial risk associated to the consumption of each unit of energy commodity or technology.

27 Here, $y = \{x\}^+$ is notation in which the $+$ indicates the value is clamped to non-negative numbers and therefore defined by the following two linear constraints $y \geq x$ and $y \geq 0$. Alternatively, this can also be noted as $\{x\}^+ \equiv Max\ (x, 0)$.

As the value of γ increases, the optimisation process seeks to reduce the consumption of $UpAbsDev$ (risk), and therefore causes the system to move away from the risk-neutral least-cost solution towards a more expensive least-cost option but with less cost-risk, thus the portfolio theory trade-off effect is modelled. Notice that when the risk aversion parameter $\gamma = 0$, the solution of Equation 3.22 is identical to the solution of a deterministic model (Equation 3.20), therefore this condition would represent the attitude of a decision maker which is indifferent to risk i.e. risk-neutral.

To illustrate the implementation of this approach in TIMES-EC, consider a simplified model that takes the uncertainty on future crude oil prices P_{OIL} and on investment price of hydropower infrastructure P_{HYD} into account. Two equiprobable scenarios (1 and 2) are considered for a certain period T. The deviations of prices (ΔP_{OIL} and ΔP_{HYD}) for these two scenarios are as follow:

SCENARIO 1:

$$\Delta P_{OIL_1}(T) = P_{OIL_1}(T) - E\left(P_{OIL_1}(T)\right)$$
$$\Delta P_{HYD_1}(T) = P_{HYD_1}(T) - E\left(P_{HYD_1}(T)\right)$$

SCENARIO 2:

$$\Delta P_{OIL_2}(T) = P_{OIL_2}(T) - E\left(P_{OIL_2}(T)\right)$$
$$\Delta P_{HYD_2}(T) = P_{HYD_2}(T) - E\left(P_{HYD_2}(T)\right)$$

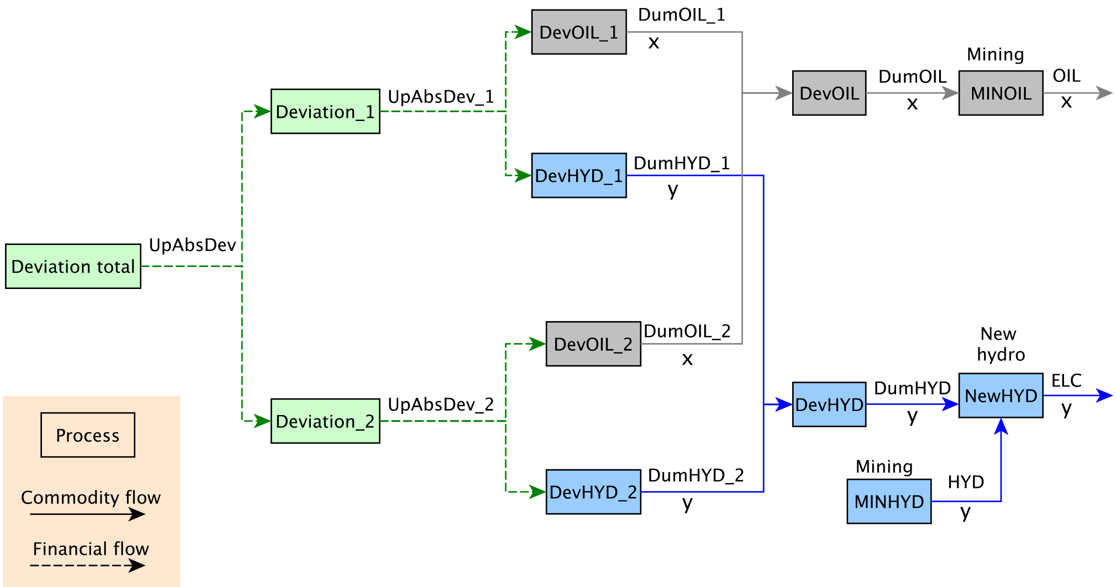
Further it is assumed that x and y are the quantity of crude oil and hydropower electricity that are consumed in this period. The $UpAbsDev$ of system costs (according to Equation 3.23) for two equiprobable scenarios in period T is then:

$$UpAbsDev = \frac{1}{2}\left\{\Delta P_{OIL_1} \times x + \Delta P_{HYD_1} \times y\right\}^+ + \frac{1}{2}\left\{\Delta P_{OIL_2} \times x + \Delta P_{HYD_2} \times y\right\}^+ \quad (3.24)$$

The implementation of Equation 3.24 in TIMES-EC for this simplified example is shown in Figure 3.28 on the following page. Auxiliary dummy input flows (arrows) of commodity (DumOIL and DumHYD) are created for each energy commodity that is consumed of crude oil (OIL) and electricity from hydropower (ELC).[28] The dashed line represents financial risk flows and solid line energy flows. To create a unit of energy commodity (DumOIL or DumHYD) a series of sub-commodities need to be aggregated (DumOIL_1, DumOIL_2 and DumHYD_1, DumHYD_2, respectively). If we consider

28 It is assumed that conversion efficiency from hydropower resource to electricity is 100%

Figure 3.28: Simplified representation of Upper Absolute Deviation auxiliary dummy flows in TIMES-EC



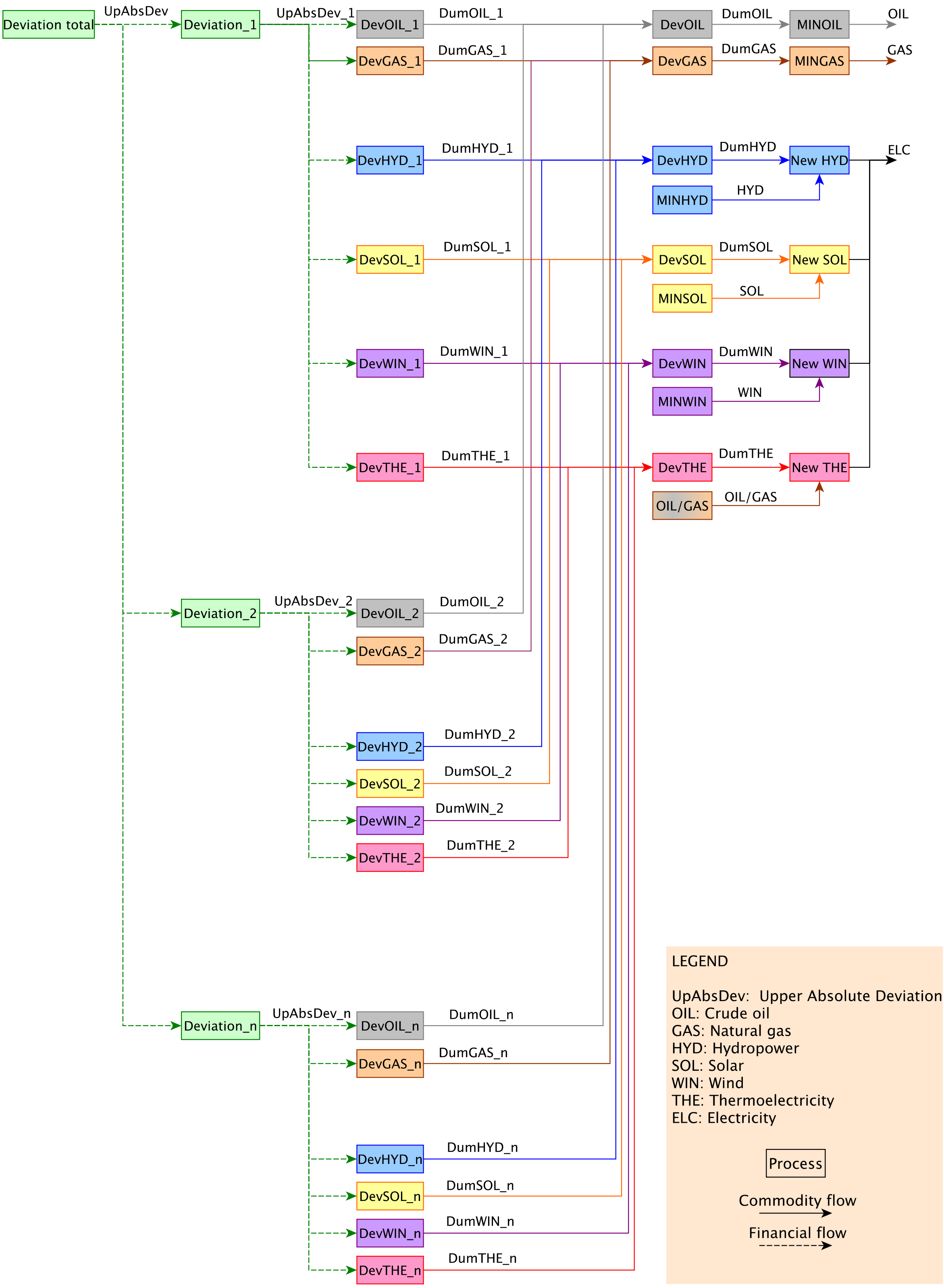
Scenario 1 for crude oil, the additional cost for consuming oil (and therefore x units of DumOIL_1) would require a financial flow of $\Delta P_{OIL_1} \times x$. Analogously, $\Delta P_{HYD_1} \times y$ would be the additional cost of consuming electricity generated from hydropower in Scenario 1. The total additional cost in Scenario 1 (UpAbsDev_1) is equal to summation of oil and hydropower electricity financial flows, i.e. $\frac{1}{2}\{\Delta P_{OIL_1} \times x + \Delta P_{HYD_1} \times y\}^+$, considering its respective probability (p_1, which in this case is 50% or $\frac{1}{2}$). Total financial flow for both scenarios $UpAbsDev$ is the sum of the additional cost of Scenario 1 and 2 (Equation ion 3.24).

Notice in Figure 3.28 that while auxiliary commodity flow of DumOIL is directly associated to the mining process of crude oil and impacts all downstream processes that consume oil, the auxiliary commodity flow of DumHYD is associated only to the new capacity additions of hydropower which would be the ones affected by investment cost risk.

This approach can be expanded to include further primary energy flows and electricity generation technologies, as can be seen in Figure 3.29 on page 166, in which the complete UpAbsDev diagram used in TIMES-EC is shown. Processes created are represented in boxes, while commodities and their flows are represented with arrows. The uncertainties assessed are fossil fuel prices (crude oil and natural gas) and four types of electricity generation infrastructure costs (hydropower, wind, solar and thermal). One-thousand scenarios of long-term prices have been created with Monte Carlo simulation, and used to populate the necessary information for deviations from expected prices, as will be explained in the following subsection.

Finally, due to the fact that there is only a single set of operational decisions, recurring uncertainty on parameters which only appear in constraints, e.g., uncertainty regarding the annual average wind speed or precipitation, cannot be integrated. The inclusion of uncertainties is restricted to parameters which directly appear in the objective function, e.g., cost elements such as fuel prices and technology costs. Therefore the impact of climate change uncertainty must be carried out separate from this approach through scenario analysis.

Figure 3.29: Full representation of Upper Absolute Deviation method integrated into TIMES-EC for n = 1,000 scenarios of fossil fuel prices and electricity infrastructure cost



3.3.2 *Uncertain parameters*

3.3.2.1 *Monte Carlo simulation with a geometric Brownian motion model*

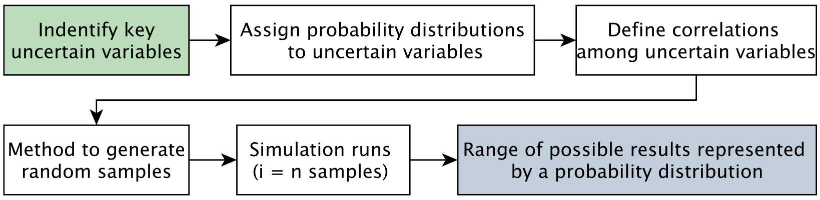
The tradition in finance for simulating correlated stock prices using Monte Carlo simulation governed by a multivariate geometric Brownian motion (hereafter GBM) evolution model is followed to simulate alternative price paths of fossil fuels and electricity generation infrastructure (Revell, 2013). The purpose of Monte Carlo simulation in this thesis is to generate (a large number of) potential future asset or commodities prices. Simulating a commodity price means generating price paths that a commodity may follow in the future. It is mentioned '*simulating commodity prices*' because future commodity prices are uncertain (called stochastic), but it is believed that they follow, at least approximately, a set of rules that can be derived from historical data and the current knowledge of commodity prices (Sengupta, 2004).

Probabilistic analysis based on Monte Carlo simulation, as stated by Damodaran (2008), can be considered as – *the most complete approach of assessing risk across the uncertainty spectrum.* It is most comprehensive yet a flexible method for analysing problems which contain many, and potentially interacting uncertainties. As mentioned by Roques et al. (2006), Monte Carlo simulation is capable of addressing many of the limitations of sensitivity analysis by assigning probability distribution functions to inputs, and to simulate the output distribution by repeating sampling. Probabilistic distributions can be determined based on historical trends or expert judgements (Usher and Strachan, 2013).

However, while one can use history and experts to define these, there is no guarantee that such distributions in any way reflect "real" distributions, especially with such long-term developments and with significant energy system transitions expected. Unlike in natural sciences, controlled experiments are unfortunately not available to define the shape of probability distribution functions of future technology costs or fossil fuel prices. There is though some limited empirical evidence from time-series analysis of historical technology data (e.g. nuclear power generation Koomey and Hultman, 2007), which suggest the use of probabilistic distributions, characterized by a tail on the upper side and a cut-off on the lower part of the costs. Similar to earlier stochastic analysis by for example Gritsevskyi and Nakićenovi (2000) we thus apply lognormal probabilistic distributions to all uncertain cost parameters where the expected values correspond to the deterministic costs.

Monte Carlo simulation techniques have been employed by a number of studies for uncertainty analysis in electricity industry investment and planning to model key uncer-

Figure 3.30: Monte Carlo simulation process



tainties such as fuel prices, carbon price, electricity and capital cost (Tekiner et al., 2010; Roques et al., 2006; Feretic and Tomsic, 2005; Vithayasrichareon et al., 2015; Pye et al., 2015). These studies are often based on stand-alone technology analysis which considers the economic viability of individual generation technologies when making investment decisions. Generation planning that is based on stand-alone technology costs is likely to lead to economically inefficient outcomes since it does not recognised the diversity value of different technologies within the generation portfolio (Awerbuch and Yang, 2007), as has been mentioned previously. The study of Pye et al. (2015) is an example of a recent study that used a probabilistic approach, combined with an integrated systematic sensitivity analysis to explore the effects of parametric uncertainty on the outputs of an energy system model for the UK. Monte Carlo simulations were used to propagate the probability distributions on input assumptions through the model. The results show that by including uncertainty in the analysis, robust decisions can be identified, as well as the technology deployments that are highly sensitive to uncertainties. In this sense Monte Carlo simulations are a tool to take into consideration a broader maps of the uncertainty surrounding certain technology and commodity costs.

A process flow of Monte Carlo simulation is shown in Figure 3.30. A single simulation involves drawing a random value from each input distribution and then calculating the system outputs. Hundreds to thousands of simulations are then undertaken to determine a probability distribution of outputs. The output is represented by a probability distribution, providing a full spectrum of possible output values subject to the actual inputs that end up being simulated. The accuracy of the outcome depends on the sample size – the larger the sample size the more accurate the result but also the longer the computation time. The statistical features of mean and standard deviation (SD) can be used to measure the cost-risk profile of the output under conditions of particular assumed probability distributions. The main drawback of Monte Carlo simulation technics is that it can be difficult to estimate both the probabilities and the interrelationships among variables in the Monte Carlo simulation model, or put in a another way, making assumptions about the assumptions (Spinney and Watkins, 1996; Roques et al., 2006).

A key step in the Monte Carlo simulation process is selecting an appropriate (stochastic) model for the time evolution of the underlying asset(s) and then simulating the model through time to generate random samples. In this study, the standard model for evolution of equity prices given by a geometric Brownian motion is used (Revell, 2013). Brownian motion is often used to explain the movement of time series variables, and in corporate finance the movement of asset prices (Brealey et al., 2011; Hull, 2003). GBMs underlying theory is that stock market prices exhibit random walk (i.e stochastic or random process). The random walk theory is the idea that stocks take a random and unpredictable path, making it near impossible to outperform the market without assuming additional risk.

Some of the arguments for using GBM to model commodity prices according to Reddy and Clinton (2016) are:

- In a GBM model expected returns are independent of the value of the stock price, which agrees with what we would expect in reality.
- A GBM model only assumes positive values, just like real stock prices.
- A GBM model shows the same kind of 'roughness' in its paths, as we see in real stock prices.
- Calculations with GBM models are relatively easy.

However, GBM is not a completely realistic model, in particular it falls short of reality in the following points:

- In real life, there are periods where prices stay on the same level, particularly true for assets with low liquidity, but GBM does not account for periods of constant values.
- In real stock prices, volatility changes over time (possibly stochastically), but in GBM, volatility is assumed constant.
- In real life, stock prices often show jumps caused by unpredictable events or news, but in GBM, the path is continuous (no discontinuity).

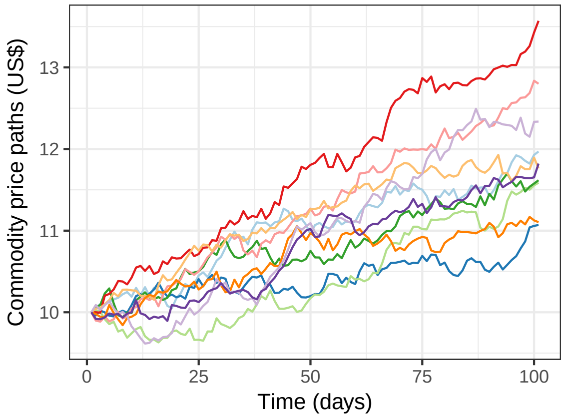
This study will use GBM to simulate paths for fossil fuel prices (oil and gas) and infrastructure capital costs. In this sense, the previously mentioned limitations of GBM would be relevant, for example, if it considered that there is a possible future in which fossil fuels are dramatically phased out, their demand and price reduce, which consequently lowers price volatility and creates a period in which fossil fuel prices are constant. Similarly, strong deployment of solar and wind technologies could keep a downward cost tendency and also coincide with low volatility. Although this is difficult to foresee, particularly the global future of fossil fuel prices, this study considers the scenario that the prices of fossil fuels will remain uncertain and volatile in the future, and the results are valid in this context. Notice however that if the low price-fossil fuel global scenario would be considered, then given the least-cost nature of the TIMES-EC model, fossil fuel technologies would be the likely choice unless constraints (political or emission) are set to avoid this.

GBM has two components; a certain component and an uncertain component. The certain component represents the return that the stock will earn over a period of time (or the expected growth rate of the price), also referred to as the drift of the stock. The uncertain component is a stochastic process including the stocks volatility and an element of random volatility (Sengupta, 2004). The GBM model incorporates this idea of random walks in stock prices through its uncertain component, along with the idea that stocks maintain price trends over time as the certain component. This latter is also a limitation of this approach that would have an impact on results. Assuming that stocks maintain price trends (i.e. assuming a constant drift), is a strong deterministic assumption on the long-term prices of fossil fuels or capital cost of technologies. In this study it has been assumed that in the long-term fossil fuel prices will continue with an upward trend, capital costs of hydropower and thermal plants will remain fairly constant and that solar and wind technologies will have a downward trend. These deterministic assumptions will be based on exogenous projections from the literature and will be further explained in the following two sections. However, is it mentioned that the main purpose of this exercise with the integration of portfolio theory is creating an uncertainty space around the price of a commodity or capital cost of a technology to which the model reacts and deems risky to invest in given the amount of financial risk associated to its use.

In mathematical terms, Brownian motion is a stochastic model in which changes from one time to the next are random draws from a normal distribution with mean 0.0 and variance $\sigma^2 \times \Delta t$. In other words, the expected variance under Brownian motion increases linearly through time with instantaneous rate σ^2. A *geometric* Brownian motion (GBM) is a continuous-time stochastic process in which the logarithm of the randomly varying quantity follows a Brownian motion (also called a Wiener process) with drift (Ross, 2014), which can be described by the stochastic stock price evolution equation:

$$S\left(\Delta t\right) = S\left(0\right) exp\left[\left(\mu - \frac{\sigma^2}{2}\right)\Delta t + \left(\sigma\sqrt{\Delta t}\right)\varepsilon\right] \tag{3.25}$$

Figure 3.31: Simulated commodity price paths with Monte Carlo simulations and Geometric Brownian Motion model



where, $S(0)$ is the stock price today, $S(\Delta t)$ the stock price at a (small) time in the future, Δt a small increment (differential) of time, μ the expected return (or growth rate), $\sigma$the expected volatility, and ε a (random) number sampled from a standard normal distribution.

Repeated use of Equation 3.25 allows multiple potential future asset return or cost paths (between now and the future) to be generated. An example of such paths (n=10) is given in Figure 3.31 (where, S_0 = US$ 10, μ = 2%, σ = 2% and Δt = 1 day). The underlying price at each time step along each path is generated by repeatedly sampling from a standard normal distribution and applying Equation 3.25.

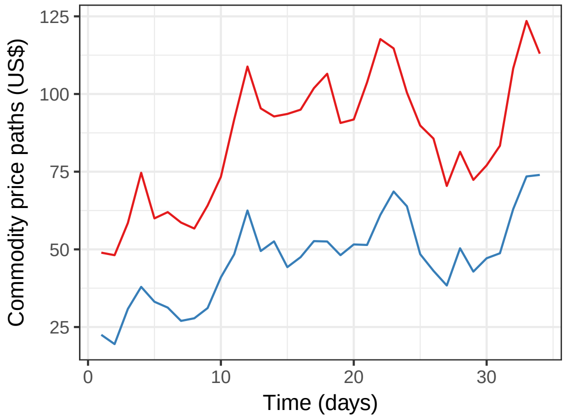
When a commodity price is dependent on a basket of underlying commodities, then multiple correlated commodity price paths must be simulated so that the simulation paths reflect the historical correlation between the commodities. The Cholesky Factorisation matrix decomposition method can be used to generate a large number of correlated random numbers, as explained by Goddard (2015). For the case of two commodities the correlated number equation collapses to:

$$\varepsilon_1 = x_1 \tag{3.26}$$

$$\varepsilon_2 = \rho x_1 + x_2\sqrt{1-\rho^2} \tag{3.27}$$

where, x_1 and x_2 are uncorrelated random numbers, which can be sampled from a random distribution in the usual way, ε_1 and ε_2 are correlated numbers, which are the numbers used to generate the commodity price paths with Equation 3.25, and ρ is the (historic) correlation coefficient between the correlated commodity prices. An example of the application of this method to simulate two correlated commodity price paths is shown in Figure 3.32 on the next page (where ρ = 0.7).

Figure 3.32: Simulated price paths for two correlated commodities ($\rho = 0.7$)



This thesis has implemented Monte Carlo simulations with GBM using the R statistical software Version 0.99.893 and code based on Revell (2013) and Systematic-investor (2012), which can be found in Appendix C on page 297

3.3.2.2 *Crude oil and natural gas price uncertainty*

Inputs for the GBM model are the starting prices in 2017, the expected annual growth rate, the individual annual volatility (standard deviation) and the underlying correlation between the price evolutions of crude oil and natural gas. This data was obtained from the U.S. Energy Information Administration Annual Energy Outlook (EIA, 2017). Annual volatility and correlation were derived from a 30-year historic annual time series of crude oil and natural gas prices, while the starting price and the expected prices of crude oil and natural gas until 2040 consider the Reference scenario, as was shown in Table 3.16 on page 150. Table 3.24 on the facing page presents a statistical summary of all mentioned variable inputs for the GBM model. Normal distributions have been used to simulate oil and gas prices.

For the Monte Carlo simulation, 1,000 price evolution scenarios for crude oil and natural gas have been simulated. This highlights the strength of Portfolio Theory for modelling recurring and correlated uncertainties, compared to a traditional stochastic approach, in which the number of scenarios that can be incorporated is much lower because of computational restrictions (Usher and Strachan, 2012), making it difficult to capture the correlations between uncertain parameters. A limitation of the approach with Monte Carlo simulation and its application to inform the portfolio theory approach is the lack of recursive action through the resolution of uncertainties in the future. In other words, the hedging here does not take into account that e.g. in 2040 we have better information about on which fuel path we are on (or what the climate change looks like, if that was included here as well) and therefore see risks differently. Here one looks at a

Table 3.24: Statistical summary of growth rate, covariance and volatility of crude oil and natural gas prices

Fuel	Price		Annual growth rate	Annual volatility	Correlated growth rate	
	2017	2050			Oil	Gas
Oil (US$/barrel)	48.90	110.30	2.50%	24%	1	0.74
Gas (US$/mill. Btu)	3.00	5.52	2.03%	35%	0.74	1

*Note: prices are West Texas Intermediate (WTI) for crude oil and Henry Hub for natural gas, annual individual volatility is the standard deviation of the price change determined from a 30-year historic annual time series (EIA, 2017).

very long-time frame and is never able to adapt the decisions based on new information. In this sense, stochastic programming has a benefit over the portfolio theory approach in the sense that it is built to react to this new information (and take into account that new information will come). However, it is highlighted that the uncertainties considered in this study are assumed as "recurring", thus meaning that they are unlikely to ever be resolved by reflecting on past occurrences or on what point in the future we might be in. For example, in 2030, the price of oil will be as uncertain as it is today and knowing how much a large hydropower plant cost, does not give any new information about the certainty on the budget compliance of the next one. It is also mentioned that the GBM model does suffer from a limitation of path dependency (i.e. an initial fixed price subject to a deterministic long-term growth rate) that will have an effect on the uncertainty distribution for the next period until the end of the simulation horizon.

3.3.2.3 *Electricity generation infrastructure cost uncertainty*

Electricity generation infrastructure cost evolution paths were carried out using 1,000 Monte Carlo simulations similar to that of oil and natural gas. Inputs for the GBM model are the investment costs in 2015 (as previously shown in Table 3.11 on page 137), the expected annual growth rate, the average cost overrun and the volatility (standard deviation) of the cost overrun. Cost overrun statistics was obtained from Sovacool et al. (2014a), who assessed construction cost overruns of 401 power plant projects developed between 1936 and 2014 in 57 countries. The statistical data obtained from Sovacool et al. (2014a) is annual growth rate (drift), volatility of cost overrun (standard deviation), and min, max and mean cost overruns registered in the sample. Based on this statistical data (mean and volatility) it was possible to generate normal distributions of cost overruns for different technologies, that was limited by the max and min cost overruns registered in the sample. Therefore, trunked normal distributions were used to simulate power technology cost prices.

Table 3.25: Statistical summary of investment cost overruns for electricity generation technologies

Type	Investment cost	Annual growth rate	Cost overrun (%)			Volatility of cost overrun
	(US$$_{2015}$/kW)	(%)	Min	Mean	Max	(%)
Hydropower plants	2,100 – 3,297	-	-50.6	70.6	512.7	111.7
Wind farms	2,200 – 2,530	-2.2	-9.1	7.7	44.4	13.1
Solar facilities	1,942 – 2,680	-2.3	-40.8	1.3	50	17.8
Thermal plants	1,190 – 2,712	-0.3 – -0.8	-50	12.6	120	33.5

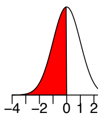
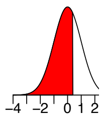
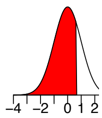
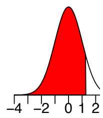
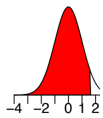
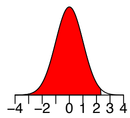
Note: Thermal plants includes those fired with fossil fuel (oil products and gas), as well as those fired with biomass, biogas and geothermal energy.
Source: Sovacool et al. (2014a)

Table 3.25 presents a statistical summary for the electricity infrastructure costs considered in this study: hydropower plants, wind farms, solar facilities and thermoelectric plants.[29] Given that the MVPT method in TIMES-EC operates with energy flows (Section 3.3.1), the technology investment costs deviations in $US/kW were converted to energy costs in $US/GWh according to the contribution that the investment cost has in the levelised cost of electricity according to Allan et al. (2011). Notice that the conversion of investment cost (in $US/kW) into a "capital variable cost" (in in $US/GWh) assumes fixed production of any given generation technology – and this is supposed to be a result of the TIMES-EC model, not an input. This could have a strong impact on gas technology, given that, for example, if the technology operates at greater capacities, its capital cost deviation impact will be smaller in its overall levelised generation cost. However, while this is true, we have also considered the deviation cost of natural gas to balance this effect, this is, while gas technology operates more and the impact of capital cost deviation falls, the deviation for operation cost rises due to the increased consumption of natural gas with uncertain prices.

No correlation was assumed among investment costs of electricity generation technologies.

29 Thermelectric plants includes: oil and gas-fired power plants, as well as those fired with biomass, biogas and geothermal energy. Nuclear hydropower and transmission cost overruns have been excluded from the analysis. Ecuador does not consider nuclear power in its long term energy policy. Transmission system average cost and their respective overruns are estimated to be relatively minor compared with those of electricity generation infrastructure (Heuberger and Dowell, 2018).

Table 3.26: Risk aversion level parameter γ and its corresponding one-sided probability values.

	Scenario					
	1	2	3	4	5	6
Risk aversion level	Risk neutral			$\longrightarrow$		Risk averse
Probability (CI)	50%	65%	75%	90%	95%	99%
						
z-score	0.00	0.39	0.67	1.28	1.64	2.33
γ	0.00	0.97	1.69	3.21	4.12	5.83

3.3.3 *Scenarios: risk aversion and climate change*

Scenarios with increasing levels of risk aversion are implemented by varying the cost (γ) attributed to the Upper Absolute Deviation, as was explained in Section 3.3.1 on page 160 (see Equation 3.22) and based on Nijs and Poncelet (2016).

Table 3.26 shows the one-sided confidence interval (CI) and the corresponding z-score[30] in case of a normal distribution of the uncertain parameter for each one of the six scenarios considered. In addition, the values for γ are shown.[31] Scenario 1 corresponds to the *risk neutral* decision maker, for which no cost overruns are considered in the optimisation run (50% one-sided confidence interval). While Scenario 6 corresponds to a *risk averse* decision maker, for which all possible probabilities of cost overrun are considered (99% one-sided confidence interval).

The Portfolio Theory approach differs from the previous section in that no policy constraints were defined. The only "policy" is the risk-taking characteristics of the decision maker, i.e. from totally risk neutral to totally risk averse. The risk perception of the policy maker will serve as a proxy for the creation of different scenarios, which in turn will impact on the least-cost technology portfolio that TIMES-EC selects. Scenarios for climate change used in the previous section will be maintained (see Table 3.4 on page 108), with the difference that the Mean scenario will be omitted, given its found similarity to the NoCC ensemble scenario.

30 In statistics, the z-score (or standard score) is the signed number of standard deviations by which the value of an observation or data point differs from the mean value of what is being observed or measured. If the population mean and population standard deviation are known, the standard score of a raw score x is calculated as: $z = \frac{x-\mu}{\sigma}$, where μ is the mean of the population and σ is the standard deviation of the population.

31 Consider the relationship: $\gamma = \sqrt{2\pi} \cdot z$ for one-sided probability value. Refer to Nijs and Poncelet (2016) for further details.

Table 3.27: Conceptual framework for integrated scenario analysis.

		Historic (No climate change)	Climate futures	
		NoCC	Dry	Wet
Risk aversion level	50% – Risk neutral			
	65%			
	75%	Baseline	Core future scenarios	
	90%			
	95%			
	99% – Risk averse			

Notice that climate change scenarios cannot be included in the portfolio theory approach because they are modelled as constraints on the availability factor of hydropower production and are not related to a cost component of the objective function. This is a limitation of the portfolio theory approach that requires to assess the uncertainty of climate change impact with a traditional scenario approach. Climate change uncertainty could very well classify as "recurring", in the sense that climate impact would cause erratic and stochastic seasons of high and low runoff and the policy maker would need to consider. However due to the limitation of the portfolio method this study considers that climate change uncertainty to be "non-recurring", meaning that, for example, once a dry climate scenario trend is in place, it is assumed that the following years will remain dry, thus assuming perfect scenario foresight for the climate component.

Table 3.27 presents the conceptual framework for the scenario analysis in this section and shows how each scenario combines risk aversion and climate futures. To focus on the impact of different risk scenarios, the results should be compared always to the risk-neutral (50% confidence interval) and NoCC climate change scenario, as a modelled "baseline" – in other words, the power system configuration and system costs that we would expect if the climate from until 2050 was similar to the historical climate and the decision maker assumes a risk neutral approach.

3.4 CHAPTER SUMMARY

This chapter discussed the methods used to assess the impact of long-term climate change and uncertainty of prices on the least-cost energy system pathway for Ecuador until 2050. It started by describing the statistical/conceptual hydrological model used to project changes in runoff, followed by a hydropower simulation model to assess the changes in electricity generation (Section 3.1 on page 91). To assess the impact on the overall energy system, the structure and assumptions for an energy system optimisation model for the Republic of Ecuador (TIMES-EC) were presented (Section 3.2 on page 110). This model focused on the power sector, because the Ecuadorian government has ambitious plans of increasing hydropower's share in the electricity mix. The power sector was modelled at the plant level with details on existing and future technologies, resources and technology prices. Demand was represented at the end-use service level, this enabled to capture different government policy targets for different economic sectors (such as introduction of electric cookstoves to reduce LPG consumption in households and the deployment of energy-intensive industries as a driver for economic development). Other sectors (transport, commercial, etc.) were modelled in a stylised way because of limited data and statistics. The chapter also presented a novel approach to assess recurring uncertainties in an energy system optimisation model (Section 3.3 on page 159). A method was presented to integrate a Portfolio Theory approach into TIMES-EC, which uses thousands of Monte Carlo simulations of fossil fuel prices and cost overruns of electricity generation infrastructure. This allows to find least-cost expansion pathways for the power sector that take into consideration the risk aversion level of the decision maker. The following chapter will present the results obtained with the presented methodology.

Part III

RESULTS AND DISCUSSION

4

RESULTS

This chapter provides results for the thesis according to the three research questions presented in the Introduction on page 3. In the first section of this chapter, the results of the climate change impact assessment on hydrological resources and the long-term hydropower electricity generation in Ecuador are detailed. The second section on page 198 will present least-cost configurations for the Ecuadorian power sector obtained with an energy system optimisation model (TIMES-EC) used to assess the impact of different policy choices and climate change scenarios. The last section of this chapter on page 4.3 will present the results of integrating a portfolio theory approach into TIMES-EC to assess the impact that the recurring uncertainty of fossil fuel prices and electricity infrastructure investment costs has on the least-cost power sector expansion pathway.

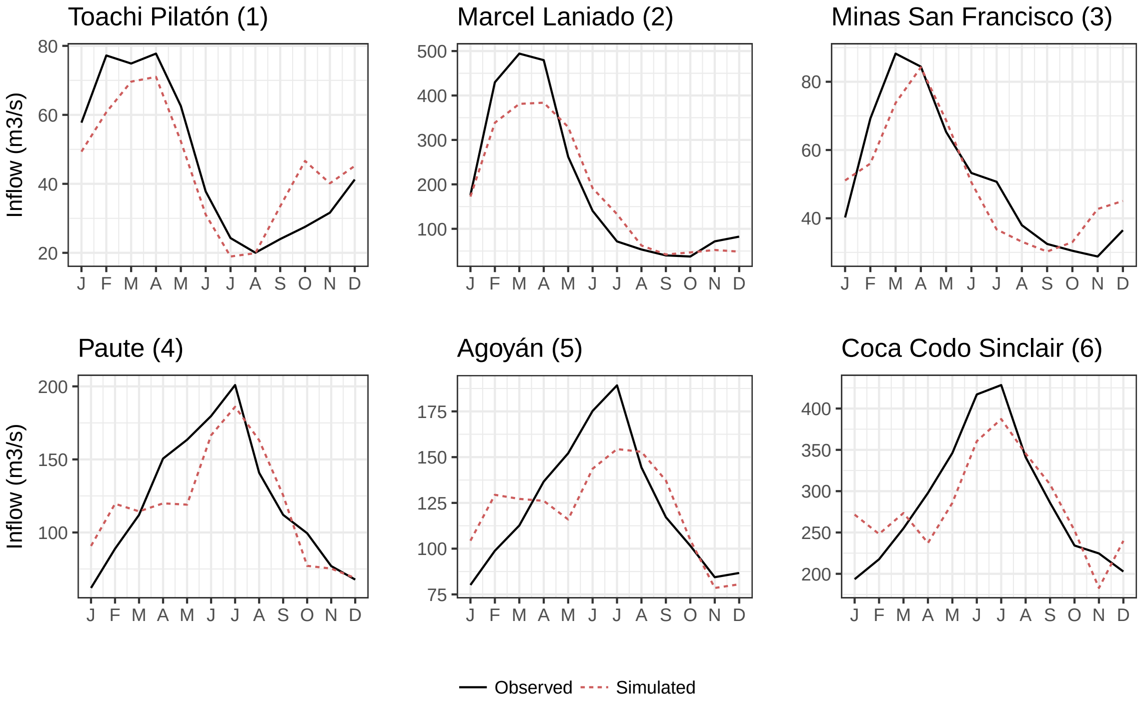
4.1 CLIMATE CHANGE IMPACT ON HYDROPOWER GENERATION

The first research question of this thesis is: *How broad is the uncertainty of hydro-climatic variables portrayed in a large ensemble of climate projections and the impact on the availability of runoff for hydropower generation?*[1]

To answer this question, a combined conceptual and statistical hydrological model was used to incorporate possible effects of climate change drawing from a large ensemble of climate projections, namely the CMIP5 modelling ensemble (see Section 3.1.1). Subsequently these results are used to assess how hydropower electricity generation could be affected by means of a hydropower simulation model (see Section 3.1.2 on page 97). The following subsections will present the validation of the used models as well as the results related to the projected changes in precipitation, run-off and hydropower generation.

1 The results of this section have been published in: Carvajal PE, Anandarajah G, Mulugetta Y, Dessens O (2017), Assessing uncertainty of climate change impacts on long-term hydropower generation using the CMIP5 ensemble – the case of Ecuador, *Climatic Change*

Figure 4.1: Observed and simulated river regimes for inflow gauging stations in Ecuador's major hydropower stations for the validation period (1971–2000).



Note: Numbers in brackets refer to the gauging stations detailed in Table 3.1 on page 104 and seen in Figure 3.2 on page 100.

4.1.1 *Impacts on water resources*

4.1.1.1 *Hydrological model validation*

Figure 4.1 shows observed and simulated river regimes for inflow gauging stations in Ecuador's major hydropower stations for the validation period (1971–2000). To validate the hydrological model, three performance statistics (Pearson's correlation coefficient – *r*, Nash-Sutcliffe Efficiency – *NSE*, and percentage deviation – *Dv*) for six hydropower stations were used. The results of these performance statistics are presented in Table 4.1 on the next page.[2]

Simulated results are classed between "excellent" and "very good" (13 out of 18 performance statistics). *NSE* for 5 gauging stations is classified as "excellent" or "very good", meaning that the model represents variations in inflow well. Relatively high values of *r* are obtained for the Pacific region, which are above or close to 0.90, however much lower *r* values are obtained for the Amazon region, with the model's performance classified between "fair" and "poor". *Dv* for all of the stations is mostly classified as "excellent" in both watersheds. The model captures the different seasonal patterns that characterise the Pacific and Amazon regions. Pacific region inflows for hydropower stations Toachi-

2 Details on gauging stations and hydropower stations used for the analysis were previously detailed in Table 3.1 on page 104 and for details on the performance statistics refer to Section 3.1.1 on page 92.

Table 4.1: Hydrological model performance statistics based on mean monthly discharges at Ecuador's largest hydropower stations for the calibration period (1971–2000).

	Hydropower station	Dv (%)		NSE		r	
	Pacific region						
1	Toachi-Pilaton	-3.27	★★★★★	0.79	★★★★	0.9	★★★★
2	Marcel Laniado	-6.7	★★★★	0.87	★★★★★	0.95	★★★★★
3	Minas San Francisco	-1.99	★★★★★	0.78	★★★★	0.89	★★★
	Amazon region						
4	Paute	-1.95	★★★★★	0.72	★★★★	0.85	★★★
5	Agoyan	-1.63	★★★★★	0.58	★★★	0.77	★
6	Coca Codo Sinclair	-1.48	★★★★★	0.67	★★★★	0.82	★★

Performance indicator	Excellent ★★★★★	Very good ★★★★	Fair ★★★	Poor ★★	Very poor ★
Dv	< 5%	5–9 %	10–14%	15–19%	≥ 20%
NSE	≥ 0.85	0.65–0.84	0.50–0.64	0.20–0.49	< 0.20
r	≥ 0.95	0.90–0.94	0.85–0.89	0.80–0.84	< 0.80

Pilaton, Marcel Laniado and Minas San Francisco have its wet season from January to June and dry season from July to December. Amazon region inflows for hydropower stations Paute, Agoyan and Coca Codo Sinclair have its wet season from April to August and dry season from September to March. This offset between regional seasonal peaks is critical for hydropower generation complementarity, however both regions share critically low flows from October to February, meaning that run-off generation capacity is restricted regardless of installed capacity. The replicability of seasonality with the hydrology model is important for further stages of climate change impacts assessment and energy modelling.

The model shows better performance for Paute, Minas San Francisco, Toachi-Pilaton and Coca Codo Sinclair, while for Marcel Laniado and Agoyan, there is underestimation of ascending limb discharges leading to *Dv* falling below the "fair" category. Agoyan shows the worst performance with regards to indicators (*NSE*: "fair" and *r*: "very poor") although *Dv* values are classed as "excellent" and *NSE* is still in the "fair" category. This is due to a period of high inflow registered during the 70s and early 2000s. Simulated peak seasonal discharges are underestimated in all cases, whilst rising and descending limbs are largely well reproduced. Overall, the model has good performance statistics that compare favourably with previous mesoscale and conceptual models for Ecuador's rivers (Buytaert et al., 2009; Crespo et al., 2012; González-Zeas et al., 2014) and other hydrological studies from abroad that have used similar performance statistics (Ho et al., 2015; Thompson et al., 2015).

4.1.1.2 *Projected precipitation and PET*

Monthly precipitation and potential evapotranspiration (PET) data for 40 GCM of the CMIP5 under RCP2.6, RCP4.5 and RCP8.5 were obtained for two 30-year periods: baseline (1971–2000) – the same duration as the calibration period for the hydrological model – and future (2071–2100) – against which baseline period values were compared by simple scaling (see Table 3.3 on page 107 for the complete list of GCMs used). This allows patterns of climate change to be expressed as the percentage change between the two time periods, also known as the delta factor approach (refer to Section 2.2.1 on page 35 and Section 3.1.1 on page 92). GCM data were downloaded from the Royal Netherlands Meteorological Institute (KNMI) Climate Explorer database using a bilinear interpolation approach and averaging precipitation and PET gridded values for each of the six basins represented in the hydrological model (Trouet and Van Oldenborgh, 2013). Data was bias-corrected using precipitation and PET values from the observed baseline period CRU datasets and using a multiplier on a monthly basis.

Figure 4.2 on page 186 and Figure 4.3 on page 186 show projected mean monthly precipitation and PET, respectively, averaged across six river basins of Ecuador for each of the 40 CMIP5 GCMs as well as for the ensemble mean for the RCP4.5. It is clear that the large amount of GCMs give rise to a large range of projections for both precipitation and PET. However, there is greater uncertainty associated with precipitation rather than PET (notice the y-axis scale in both figures). Projected changes in mean annual precipitation is different according to each basin and varies on a monthly basis in average between a decline from 100 mm to close to 0 mm for the month of July to an increase from 300 to close to a maximum 800 mm in the month of October. Notice the particular *bi-modal* precipitation profile in Ecuador with two rainy seasons, one in April and a second in October. In contrast, PET shows a much more constant value throughout the year and smaller uncertainty for all the GCMs with the magnitude of these increases varying between 40.0 mm and 130 mm, while average is around 100 mm.

The CMIP5 ensemble mean (red dashed line) projects an increase in precipitation from the baseline in most months, except during the months of September and October. At this time decreases are, however, small and average only -4.0 mm or -1.4%. The average monthly precipitation increase for the remaining months is 7.7% with the greatest increase occurring in February (+28 mm/+9.7%). Overall mean annual precipitation for the ensemble mean increases by 185 mm (+6.7%). The CMIP5 ensemble mean projects a consistent increase in PET from the baseline across the year. On average monthly PET increases by 4.1 mm (4.0%) contributing to an annual total increase of 49.5 mm (4.0%). The largest monthly PET increase of 5.27 mm (5.2%) occurs in September.

Results for 40 GCMs under the RCP4.5 scenario from the CMIP5 have been so far presented. It must be mentioned that, the framework applied in this thesis was also applied for the RCP2.6 and RCP8.5 scenarios, however differences among RCPs (intra-model) were found to be smaller compared to inter-GCM (inter-model) differences. Inter-GCM uncertainty range was also found to have similar magnitude for all three concentration scenarios. This can be seen in Figure 4.4 on page 187, which presents downloaded precipitation and PET values for individual GCMs, the ensemble mean and the historic average for the Paute river basin and RCP2.6, RCP4.5 and RCP8.5.

It is observed in Figure 4.4 on page 187, that the range of disagreement among individual GCMs is similar in all three RCPs and performing the analysis for the three RCPs would have added little to the findings. It was found in the literature that when the focus is on assessing inter-GCM uncertainty only one RCP is considered, for example in the study of Ho et al. (2015) and Thompson et al. (2015), who assess GCM-related uncertainty and use only the RCP4.5. However, when wanting to assess intra-model uncertainty and the limits of the RCP scenarios, usually RCP2.6 and RCP8.5 are considered while using the ensemble mean, for example in the studies of Samaniego et al. (2016) and van Vliet et al. (2016b). The literature mentions that inter-GCM related uncertainty rather that intra-model uncertainty is the main source of uncertainty for regional climate change scenarios (Escobar et al., 2011), therefore the focus of this thesis is mapping inter-GCM uncertainty using only one concentration scenario (i.e. RCP 4.5).

Another reason to use only one concentration scenario, is that the RCP4.5 is the scenario that gathers more GCM models. RCP4.5 contains results from 41 GCMs compared to 26 GCMs for the RCP2.6, 17 GCMs for RCP6.0 and 30 GCMs for RCP8.5 (van Oldenborgh et al., 2013). Considering that the discrepancy of GCM models is to be assessed, the GCM scenario that has the most modelling results is chosen, i.e. RCP4.5. A final reason to use the RCP4.5 is that it is considered to represent a central estimate of future climate impacts (Thomson et al., 2011) and also most closely aligns with the core objectives of the United Nations 2015 Paris Agreement (UNFCCC, 2015a), which include limiting anthropogenic warming to no more than 2°C above pre-industrial values by 2100 (IPCC, 2013).

Figure 4.2: Mean monthly precipitation in six basins in Ecuador for the baseline, individual GCMs and the ensemble mean of the CMIP5 RCP4.5 (2071–2100)

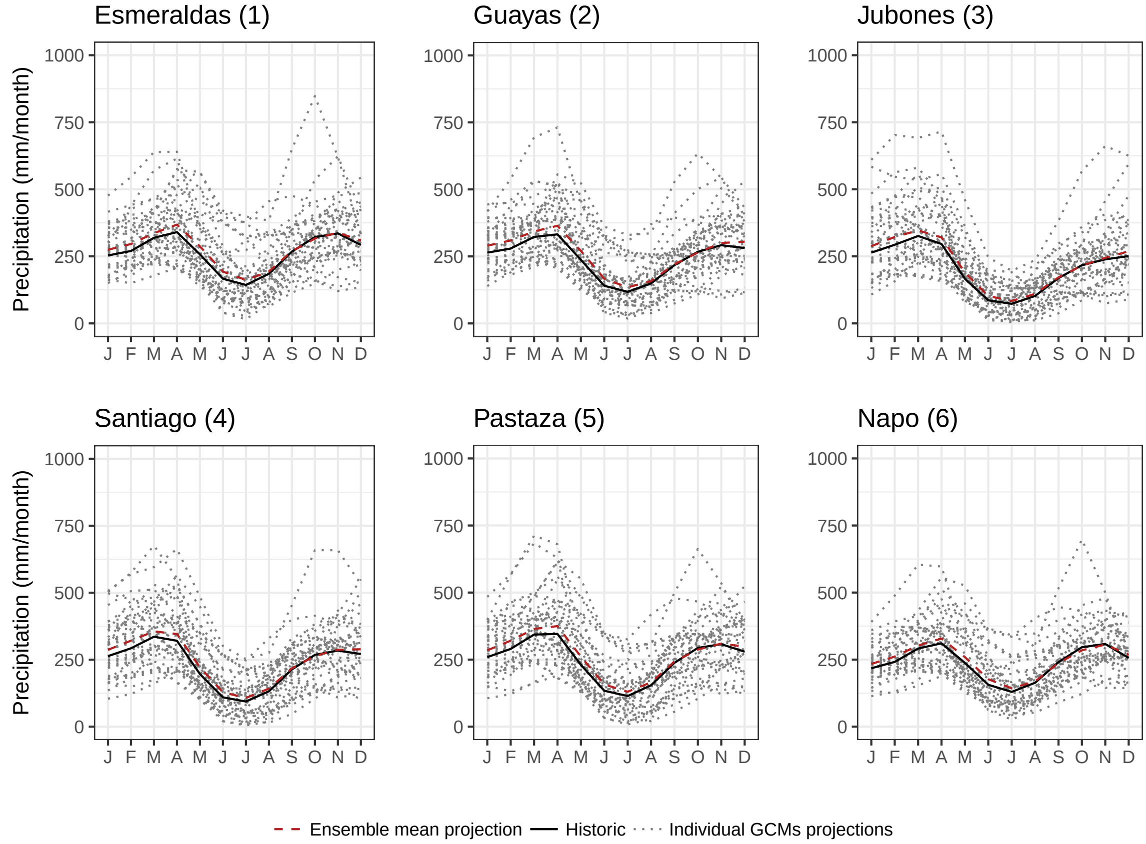


Figure 4.3: Mean monthly potential evapotranspiration (PET) over six basins in Ecuador for the baseline, individual GCMs and the ensemble mean of the CMIP5 RCP4.5 (2071–2100)

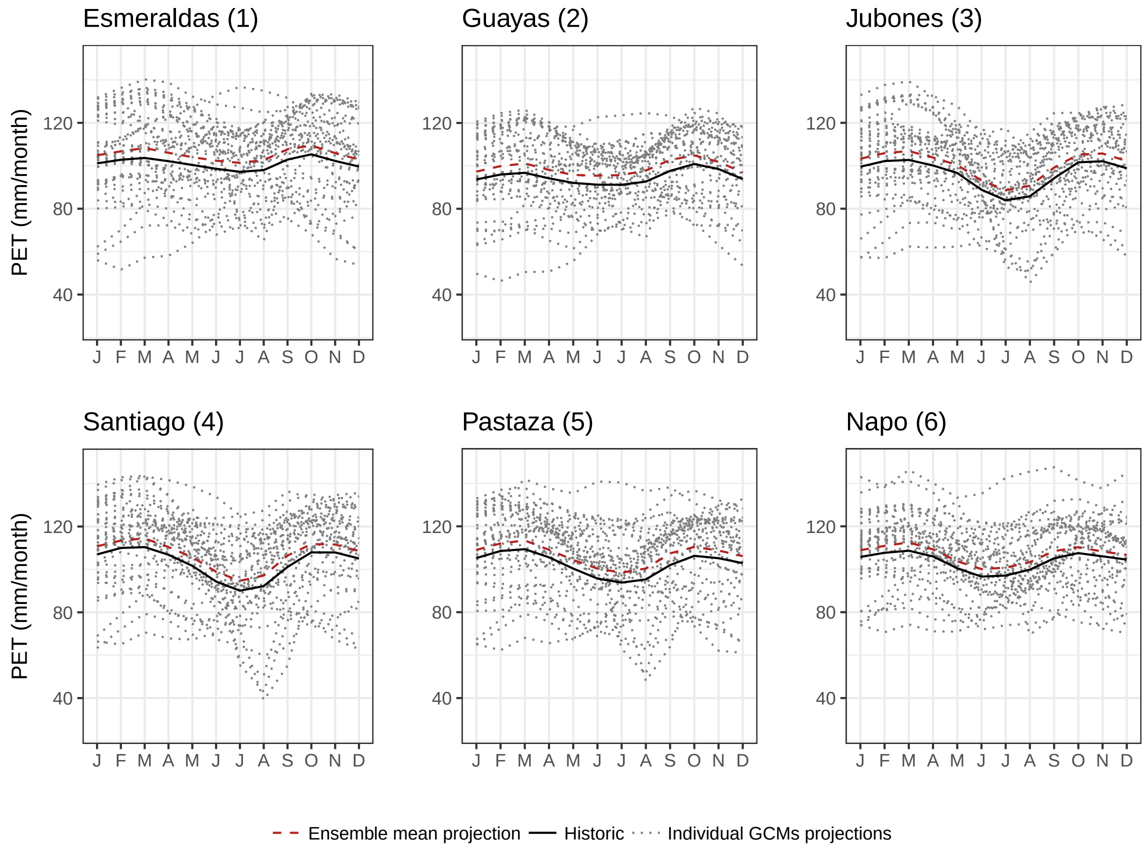
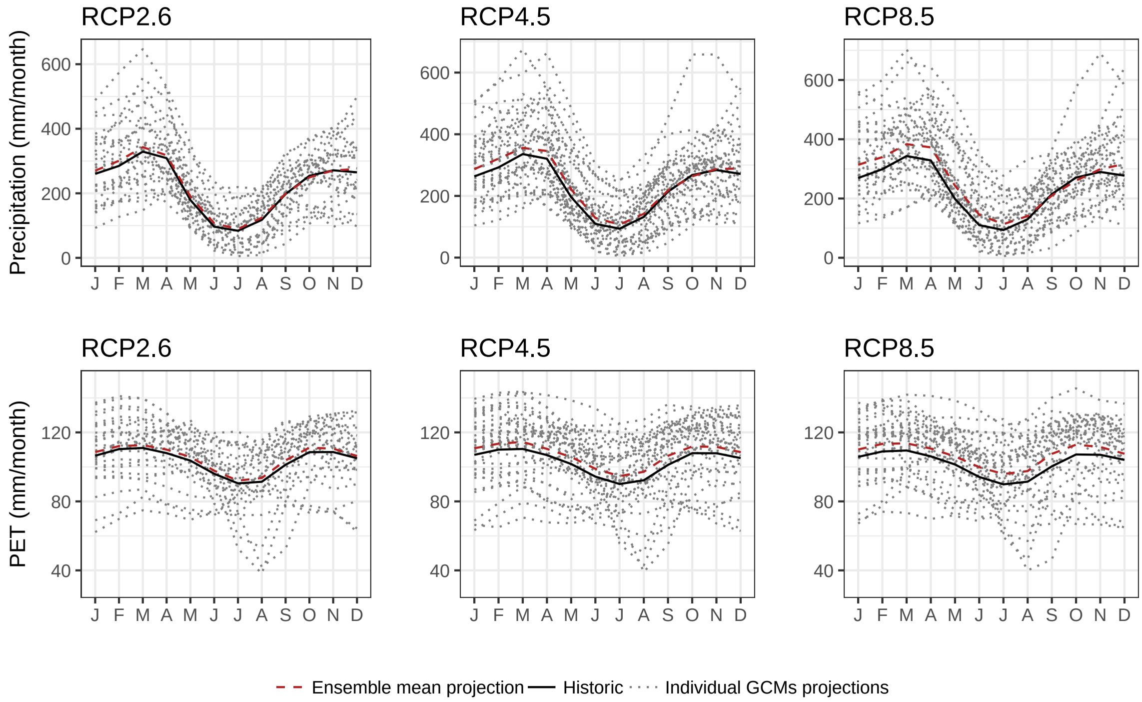


Figure 4.4: Comparison of precipitation and potential evapotranspiration in the Paute basin of Ecuador for individual GCM projections of the CMIP5 ensemble under three different RCPs and period 2071–2100.

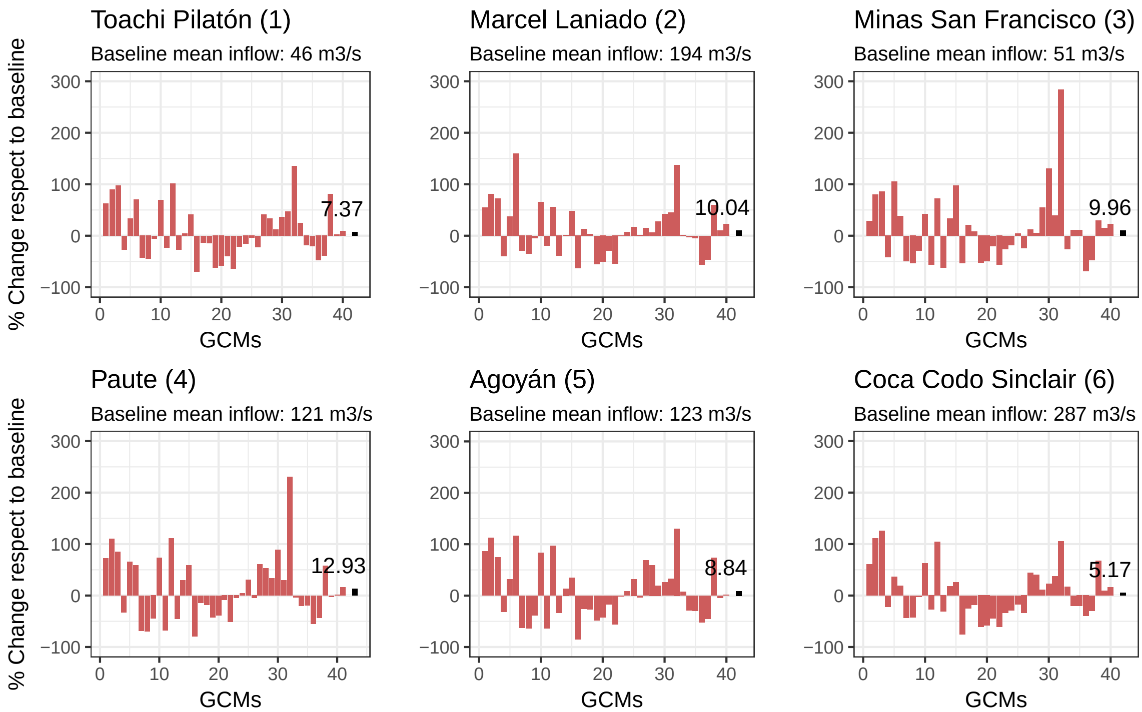


4.1.1.3 *Projected river discharge*

Hydrological simulations were conducted for the ensemble mean and each individual GCM. The impact of climate change on the average annual and seasonal inflow into hydropower stations was analysed relative to the baseline period. Figure 4.5 on the next page shows the projected mean annual inflow percentage changes compared to the historic baseline for 40 GCMs of the CMIP5 under RCP4.5 and the ensemble mean (black bar at the end of x-axis). The significant range in GCM projections presents a large uncertainty in the projected unregulated annual inflow to hydropower stations. This justifies the use of a multi-model ensemble in order to capture this uncertainty (Knutti and Sedláček, 2012; Kundzewicz et al., 2018). The inter-GCM range of projections is extremely large, maximum deviations from the mean span from -82% for the GFDL-CM3 (GCM no. 17) in Agoyan to +277% for the IPSL-CM5A-LR (GCM no. 32) in Minas San Francisco. A summary of results and statistics for projected annual inflow is shown in Table 4.2 on page 189.

It would be expected that a particular GCM projects a consistent increasing or decreasing trend for a relatively small geographical area such as Ecuador. However, there is considerable variability in the climate change signal amongst the gauging stations. The GISS-E2-R p2 model (GCM no.25), for example, suggests mean annual increases in hydropower stations Marcel Laniado, Minas San Francisco, Paute and Agoyan but

Figure 4.5: Percentage change in the mean annual inflow at Ecuador's major hydropower stations for the period 2071–2100, compared to the baseline 1971–2000, for each CMIP5 GCM under scenario RCP4.5.



Note: GCMs along the x-axis are ordered according to Table 3.3 on page 107. The ensemble mean is the black bar at the end of the x-axis.

decreases for Toachi-Pilaton and Coca Codo Sinclair. In general, for the six gauging stations, out of 40 GCMs, 22 GCMs simulate an increase in mean annual discharge, the remaining 18 projecting decreases. This is why the enemble mean in general shows an increase in inflow. This coincides with the ensemble mean projecting an increase in mean annual discharge since there are more models that agree on increase compared to decrease. However, given that all GCMs are considered equiprobable, this does not entail that there is a higher probability of increased inflow (Smith and Petersen, 2014). Of the 22 models that project an increase in mean annual discharge, 16 suggest that discharge will increase by more than 25%. In contrast, 12 our of 18 of the GCMs suggest decreases in mean annual inflow larger than 25%. This indicates that most models suggest considerable differences (< or > 25%) from the ensemble mean, which leads to the ensemble mean in all cases projecting annual increases.

Mean annual flow is a convenient indicator to assess overall impacts of climate change on a river basin, however it is insufficient and simplistic when used in isolation (Gosling et al., 2011). Changes in maximum and minimum flows and changes in seasonal patterns require at least a monthly time-step analysis, particularly to identify flood risk during high flows and to assess impacts of low flows on run-off hydropower yield. To assess the

Table 4.2: Summary of results for annual projected inflow into Ecuador's largest hydropower stations for the CMIP5 ensemble under the RCP4.5 for 2071-2100

Region	Pacific			Amazon		
Basin	Esmeraldas	Guayas	Jubones	Paute	Pastaza	Napo
Hydropower station	Toachi Pilaton (1)	Marcel Laniado (2)	Minas S. Francisco (3)	Paute (4)	Agoyan (5)	C.C. Sinclair (6)
Historic annual flow (1971-2000)						
(m^3/s)	46	194	51	121	123	287
Statistics for projected flow (2071-2100) compared to historic						
Mean (%)	7.3	10.1	9.9	12.9	8.8	5.1
Min (%)	-69.6	-63.5	-68.6	-79.3	-82.0	-75.3
Max (%)	135.1	159.5	277.0	230.3	130.7	125.4
Std. dev. (%)	51.6	50.4	67.6	63.0	57.0	51.1

differences between projected (2071–2100) and historic seasonal inflow values, Figure 4.6 on the following page is presented.

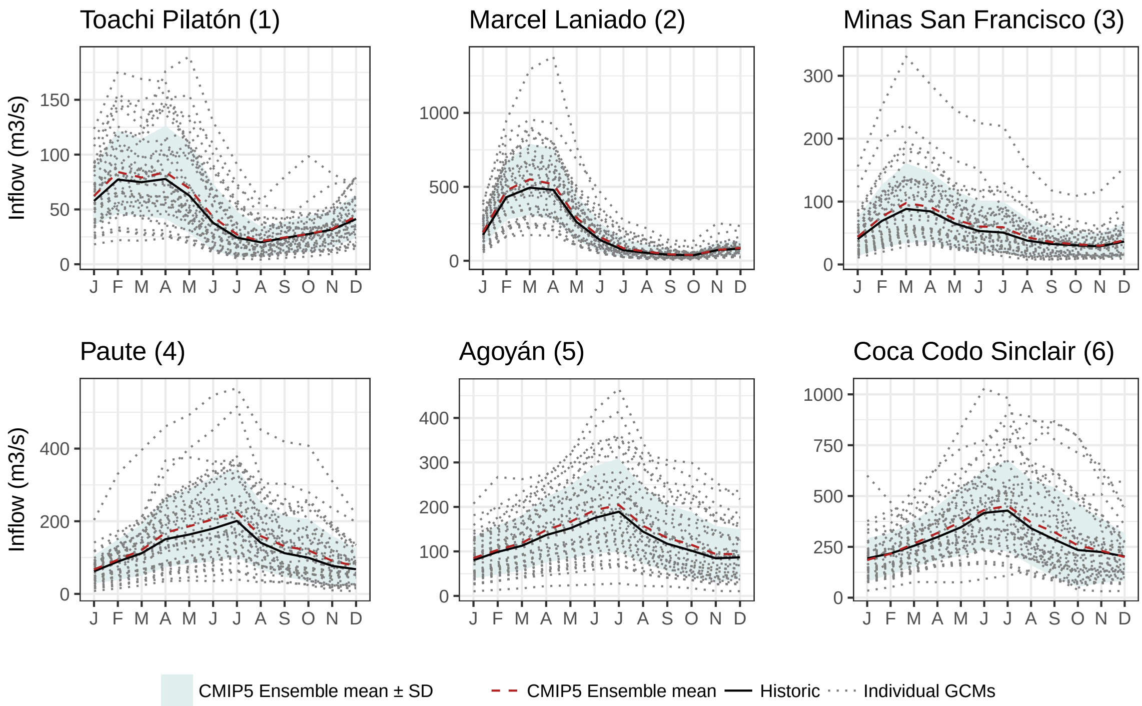
Inflow regimes for the CMIP5 ensemble mean (red dashed line) show that mean monthly discharges throughout the whole year are slightly higher than those of the baseline for the wet season for both watersheds, but mean monthly projections are rather close to the baseline during the dry season from October to January. Coca Codo Sinclair is the only station for which the ensemble mean decreases from December to February. Seasonal characteristic patterns seem to be maintained by most of the GCMs projections. Uncertainty is greatest in the wet season, with some GCMs doubling or tripling the baseline inflow but others remaining closer to the baseline values. However, analysing results according to wet and dry seasons, it is found that during the wet season 62% of the GCMs agrees on increases, while during the dry season 55% of GCMs agree on decreases of inflow. This corroborates the projections for the region having wetter wet seasons and drier dry seasons under climate change (Kundzewicz et al., 2007).

4.1.2 *Impacts on hydropower generation*

4.1.2.1 *Hydropower simulation model validation*

To validate the model, simulated hydropower production was compared to observed generation of four different types of hydropower facilities within these systems, i.e. single/cascading and run-of-river/reservoir. Figure 4.7 on page 191 compares simulated to observed monthly electricity production. The close fit between simulated and observed hydropower production shows that the aggregated global results give a good

Figure 4.6: River inflow regimes for gauging stations at Ecuador's major hydropower stations. The historic baseline, each GCM of the CMIP5 and the ensemble mean under the RCP4.5 scenario for the 2071–2100 period is shown.



Note: The shaded band represents the standard deviation

indication of reality. The hydropower simulation model performance has been validated similar to Yi Ng et al. (2017), with two statistical measures i) Pearson's correlation coefficient (r) and ii) standard error (e). Table 4.3 on the facing page presents validation results and shows that Pearson's correlation scores for observed versus simulated hydropower production demonstrate reasonable to strong performance for most hydropower stations in average a value of 0.9. Standard error is also low in average 1.2% of the value of total monthly generated electricity.

4.1.2.2 *Projected variation on hydropower generation*

Figure 4.8 on page 192 presents aggregated results for electricity generation of the selected hydropower systems which have a total installed capacity of 4,368 MW (>80% of Ecuador's current total installed capacity, see Section 3.2.2). The Wet scenario presents an overall higher electricity output throughout the year; the wet season (March to August) presents a 15% average increase, while the dry season presents an average increase of 46%. In contrast, the Dry scenario presents an average reduction of -50% during the wet season and of -76% for the dry season. Hydropower stations Coca Codo Sinclair, Toachi-Pilaton, and Minas San Francisco do not have any output at all in the dry season of the Dry scenario. Paute and Agoyan maintain output in the Dry scenario due to

Figure 4.7: Simulated versus observed monthly hydropower production for four hydropower stations representing different types of hydropower stations in Ecuador

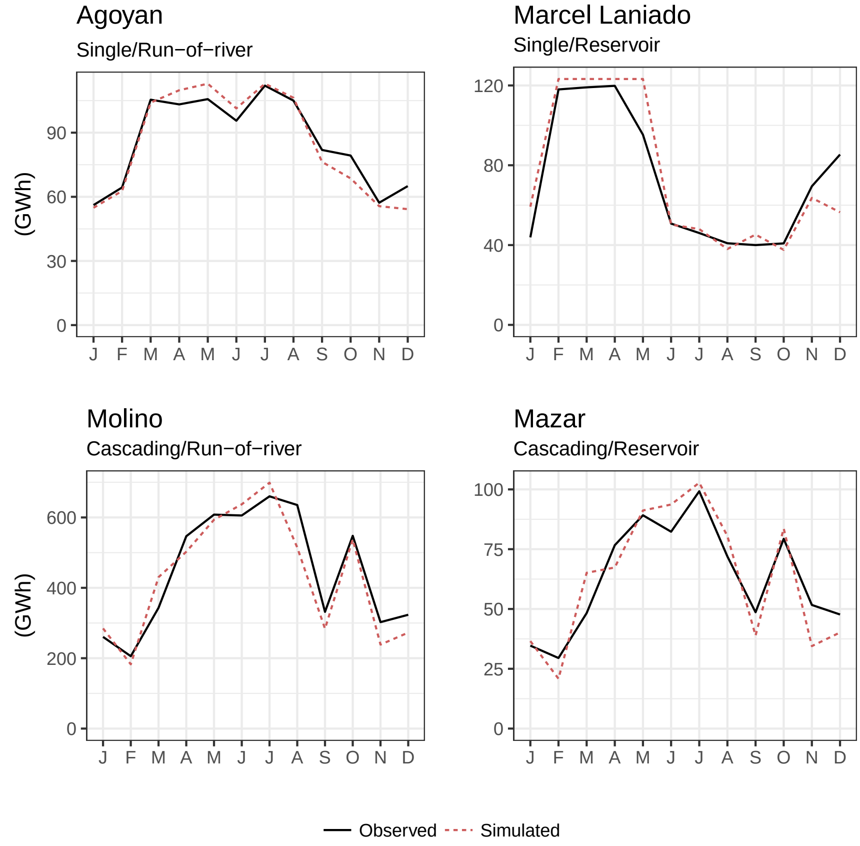


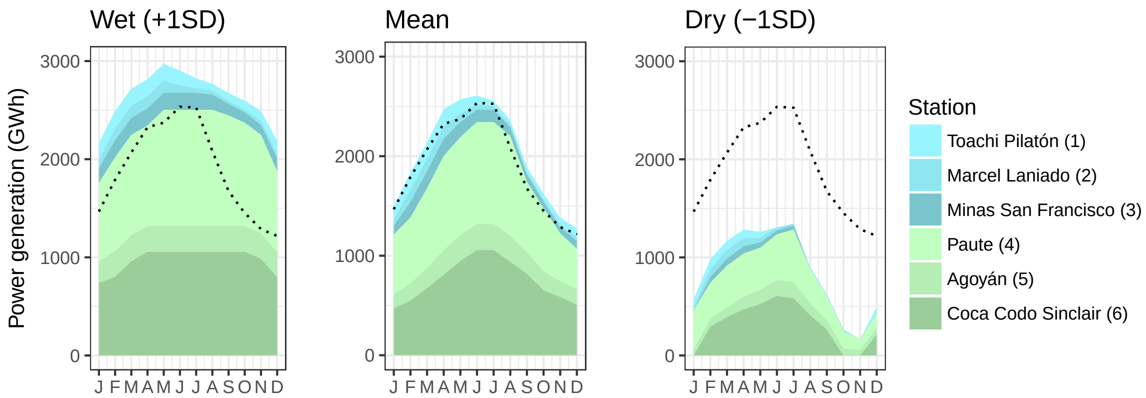
Table 4.3: Fit diagnostics for hydropower electricity output model for calibration period (2012–2015)

Hydropower station	Type*	Average gen. (GWh)	r		St. error (GWh / %)	
Paute Mazar	Cascading/Dam	800	0.88	★★★	10.1 / 1.2	★★★★★
Paute Molino	Cascading/ROR	4,900	0.89	★★★	58.2 / 1.1	★★★★★
Marcel Laniado	Single/Dam	717	0.87	★★★	13.9 / 1.9	★★★★★
Agoyan	Single/RoR	1,080	0.96	★★★★★	5.1 / 0.5	★★★★★

Performance indicator	Excellent	Very good	Fair	Poor	Very poor
	★★★★★	★★★★	★★★	★★	★
r	≥ 0.95	0.90–0.94	0.85–0.89	0.80–0.84	< 0.80
St.error	<5%				

Note: ROR is run-of-river, DAM is hydropower with reservoir

Figure 4.8: Seasonal projection of power generation for selected hydropower stations considering mean and standard deviations according to the RCP4.5 of the CMIP5 ensemble for the 2071–2100 period.



Note: The dotted line is the aggregated historical generation. The Amazon watershed is coloured in green and the Pacific watershed is coloured in blue.

their regulation capacities. Marcel Laniado seems less affected by inflow variations due to its large reservoir. Table 4.4 on the facing page presents results at the annual level and percentage deviations from annual observed generation values for the aggregated hydropower system (22,801 GWh/yr.), showing a 6% increase (1,408 GWh) for the ensemble mean, +39% increase (800 GWh) for a Wet scenario, while a significant reduction of -55% (-12,400 GWh) for the Dry scenario.

In addition to quantifying seasonal and annual long-term impacts of climate change on the current installed hydropower capacity of Ecuador, the hydropower model was used to calculate the changes in availability factors of these representative hydropower stations. Figure 4.9 on page 194 presents the availability factors derived from the hydropower model. Availability factors follow seasonal inflow patterns (compare to Figure 4.6 on page 190) and its variation range depends on storage and operational characteristics of the representative hydropower stations. Cascading hydropower stations in the same river have been aggregated given that they usually are considered as one integrated system. An optimistic or Wet scenario increases the monthly availability factors (85–89%); however, the pessimistic or Dry scenario presents a more critical situation: monthly availability factor dropping to a value of 0% during the dry season, namely for the stations that have small regulation capacity e.g. Coca Codo Sinclair, Minas San Francisco and Toachi-Pilaton. Marcel Laniado which has a large reservoir (1,733.6 Hm^3) presents less sensitivity to changes, although in the Dry scenario drops likewise to zero at the peak of the dry period in November.

Table 4.5 on page 194 presents the historic (30-year average, 1971–2000) annual availability factor as well at the projected availability factors for the Mean (ensemble), Wet and Dry scenarios until 2050. The relative changes of the climate scenarios compared

Table 4.4: Annual generation output changes for the RCP4.5 ensemble mean, +1SD and -1SD for 2071-2100

Basin	Hydropower station	Capacity (MW)	Generation (GWh/yr.)	Climate change 2071-2100 Δ		
			Historic	Dry (-1SD)	Mean	Wet (+1SD)
Pacific region						
1 Esmeraldas	Toachi-Pilaton	255	1,120	-59%	9%	41%
2 Guayas	Marcel Laniado	213	717	-36%	5%	25%
3 Jubones	M.S. Francisco	275	1,290	-73%	7%	43%
Amazon region						
4 Santiago	Paute	1,757	8,500	-52%	8%	46%
5 Pastaza	Agoyan	368	2,480	-48%	6%	29%
6 Napo	C.C. Sinclair	1,500	8,734	-57%	4%	34%
Total system		4,368	22,841	-55%	6%	39%

Note: Cascading hydropower systems have been aggregated: Toachi-Pilaton (Toachi 205 MW and Pilaton 50 MW), Paute (Mazar 170 MW, Molino, 1,100 MW and Sopladora 487 MW) and Agoyan (Agoyan 156 MW and San Francisco 213 MW)

to the historic are also shown. The total average availability factor has been included at the bottom row of Table 4.5 on the following page to give a sense of the deviations for the entire system. The Mean scenario represents a slight increase in the availability factor (4%), while the Wet scenario registers an increase of +19% and the Dry scenario a reduction of -25%. These results will be used in TIMES-EC to characterise the variation of hydropower output in six river basins that have been depicted in the energy system model. Figure 4.10 on page 195 and Figure 4.11 on page 196 show the projected availability factors in 2050 and 2085 (2071-2100), respectively; according to the model's attribute format which was discussed in Section 3.2.5 on page 124 and can be seen in Figure 3.15 on page 130.

Figure 4.9: Mean monthly availability factors for Ecuador's major hydropower stations for the historic period (1971-2000), the ensemble mean and the standard deviation of the CMIP5 RCP4.5 scenario for the period 2071-2100

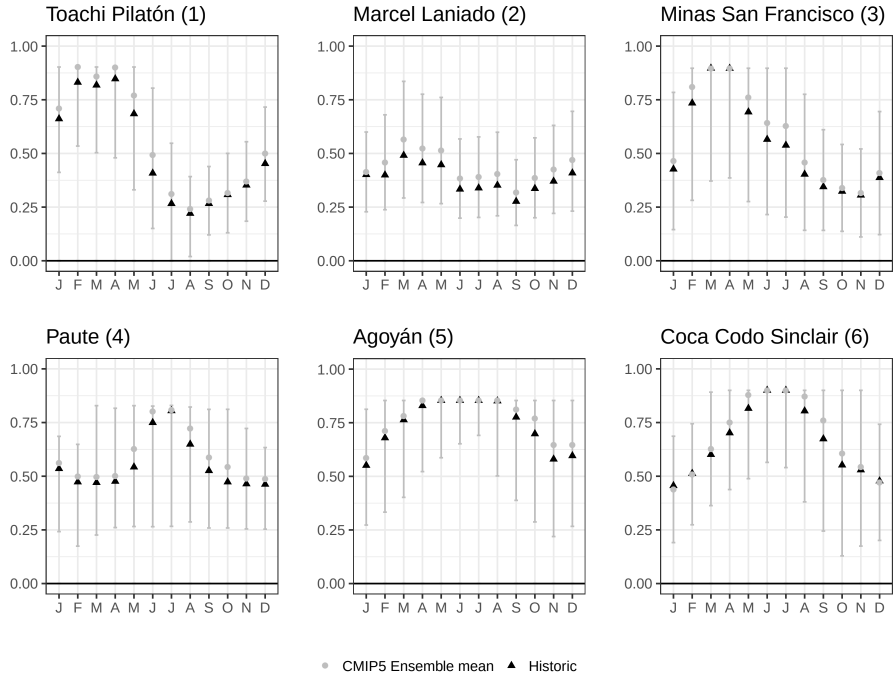
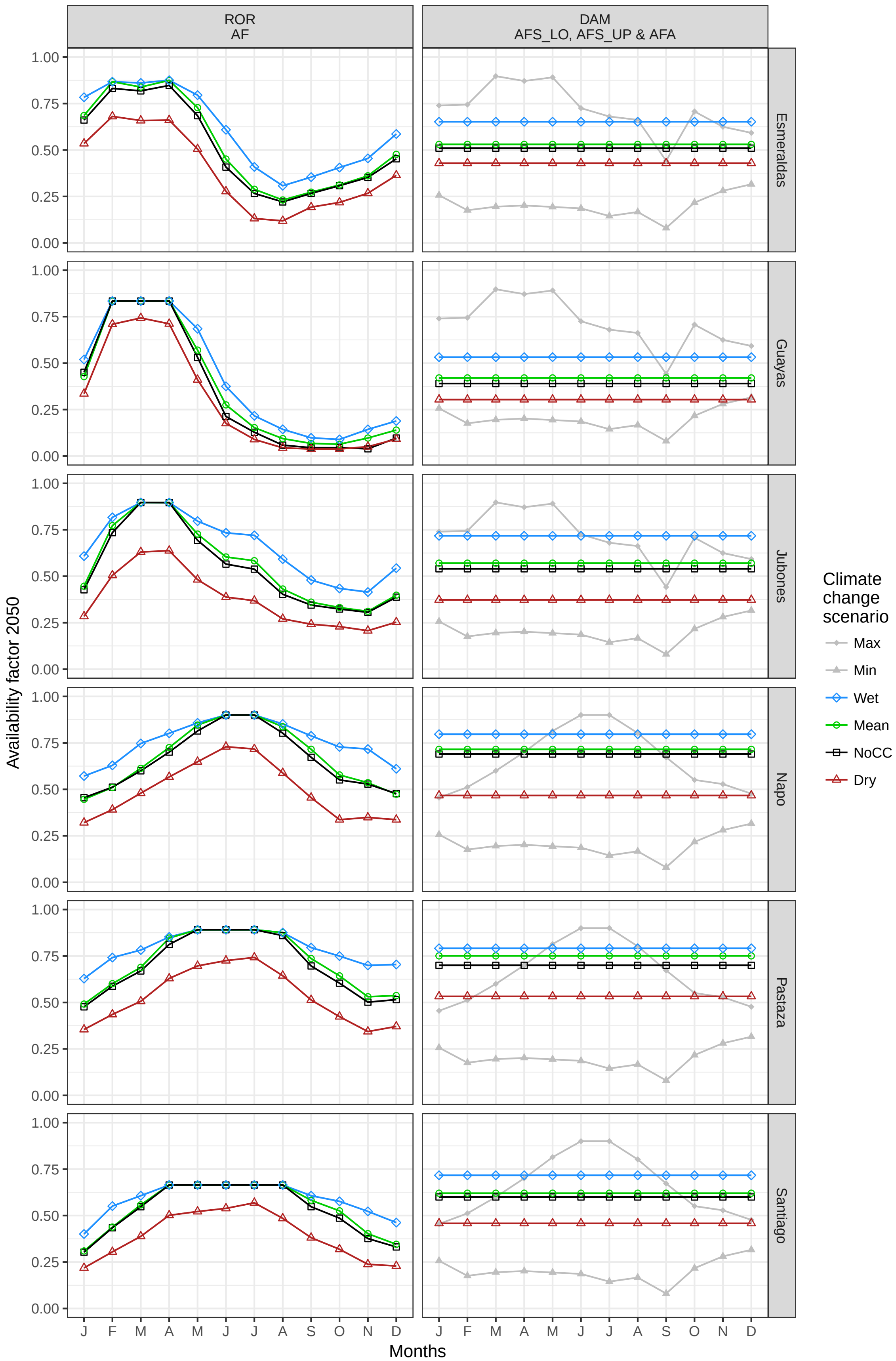


Table 4.5: Projected annual availability factors for hydropower stations in Ecuador's main river basins

Basin	1970–2000 Historic AF	Climate 2050 Wet AF	Wet Δ	Mean AF	Mean Δ	Dry AF	Dry Δ
Pacific region							
Esmeraldas	0.52	0.61	19%	0.53	4%	0.39	-24%
Guayas	0.38	0.52	34%	0.41	7%	0.31	-20%
Jubones	0.54	0.66	21%	0.56	4%	0.38	-31%
Amazon region							
Santiago	0.55	0.66	20%	0.57	4%	0.40	-27%
Pastaza	0.74	0.80	7%	0.75	2%	0.58	-21%
Napo	0.66	0.76	15%	0.67	2%	0.50	-25%
Total average	0.57	0.67	19%	0.58	4%	0.43	-25%

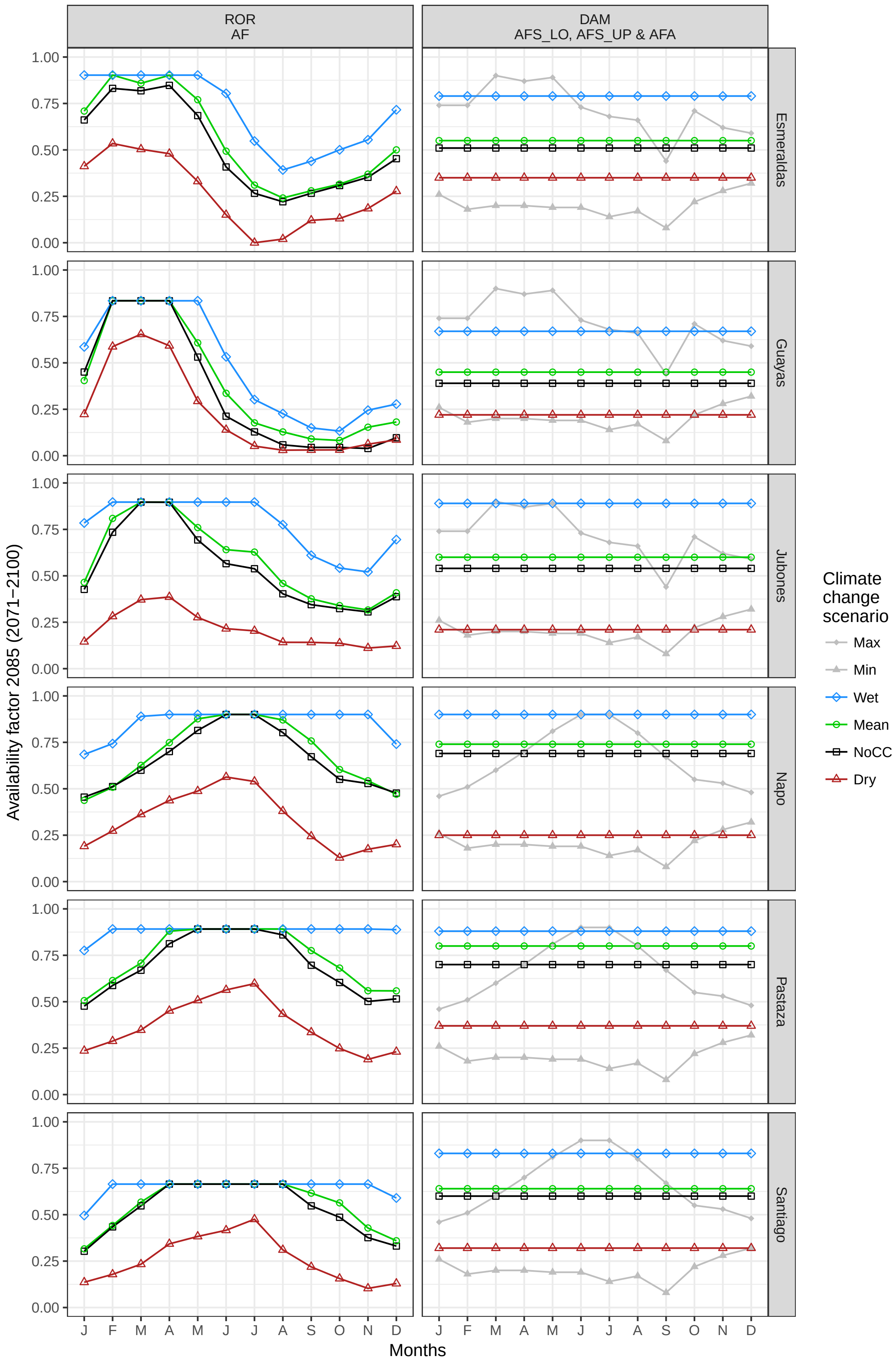
Note: AF is the annual average availability factor. Δ is the availability factor change of the Mean, Wet and Dry scenarios respect the Historic.

Figure 4.10: Projected availabilty factors of hydropower stations according to basin in Ecuador in 2050 (TIMES attribute format)



Note: ROR hydro is represented in TIMES-EC with fixed availability factor (AF), DAM hydropower is represented with annual availability factor (AFA), and seasonal flexible availability factors (AFS_LO and AFS_UP). Refer to Section 3.2.5 on page 124 for details.

Figure 4.11: Projected availabilty factors of hydropower stations according to basin in Ecuador in 2085 (TIMES attribute format)



Note: ROR hydro is represented in TIMES-EC with fixed availability factor (AF), DAM hydropower is represented with annual availability factor (AFA), and seasonal flexible availability factors (AFS_LO and AFS_UP). Refer to Section 3.2.5 on page 124 for details.

4.1.3 *Summary*

This subsection has provided a climate change impact assessment of hydropower generation in Ecuador. It conclusively demonstrates that there is large disagreement among GCM projections regarding the impact that climate change will have on the change of magnitude and sign of change of precipitation in the long-term. This has implications for the expected availability of runoff for hydropower generation. Specifically, it was found that annual generation of the largest hydropower stations in Ecuador (4,368 MW) can change significantly under different scenarios of climate change by the end of the century (2071-2100). Results for the RCP4.5 concentration scenarios show a 6% increase in power generation when using the CMIP5 ensemble mean, +39% increase for a Wet scenario (+1 SD of the ensemble), while a significant reduction of -55% for a Dry scenario (-1 SD of the ensemble), as shown in Figure 4.8 on page 192.

Selected key outcomes of this subsection are summarised below (while all key findings are restated in the conclusion of this thesis in Chapter 6 on page 271):

- Long-term projections of precipitation and potential evapotranspiration encompass a wide range, dominated by the large differences among individual GCMs (inter-model) projections. Inter-model GCM uncertainty range was also found to have similar magnitude for all three concentration scenarios (RCP2.6, RCP4.5 and RCP8.5). Differences among the RCPs (intra-model) were found to be smaller compared to the difference among individual GCMs (inter-model). This can be seen in Figure 4.4 on page 187. Performing the analysis for the three RCPs would have added little to the findings. Assessing individual GCMs under a single RCP allows to characterise a broader uncertainty space of the possible effects of climate change on water resources.

- The large amount of GCMs of the CMIP5 ensemble projections give rise to a wide range of projections for both precipitation and potential evapotranspiration (PET). Figure 4.2 on page 186 and Figure 4.3 on page 186 show projected mean monthly precipitation and PET, respectively, averaged across six river basins of Ecuador for each of the 40 GCMs of the CMIP5 ensemble. The range of precipitation change uncertainty spans from 0 to 800 mm/month, while PET uncertainty spans from 40 to 140 mm/month.

- The inter-GCM uncertainty range of precipitation and PET has an impact on the projected unregulated annual inflow into hydropower stations in Ecuador. Maximum deviations from the annual mean historical inflow into Ecuadorian hydropower stations towards the end of the century span from -82% to +277%. This can be seen in Figure 4.5 on page 188.

- The change in hydropower output due to different climate change scenarios for Ecuador's main hydropower stations has been translated to availability factors that represent six river basins in the country, as can be seen in Table 4.5 on page 194. The historic (1971-2000) average annual availability factor of the hydropower system is 57%, a scenario that considers the RCP4.5 ensemble mean of the CMIP5 by 2050 would increase the availability factor to 58%, while a Wet scenario (+1 SD of the CMIP5 ensemble) would increase it to 67% and a Dry scenario (-1 SD of the CMIP5 ensemble) would reduce it to 43%. This change in hydropower output can also be seen in Figure 4.8 on page 192 where monthly hydropower generation in the largest hydropower stations in Ecuador is compared for different end-of-the-century climate change scenarios and historic generation. Dry scenarios could reduce runoff to a point in which hydropower stations reach zero production for continuous months during the dry season of the year (October to January).

The next section will present power sector development pathways until 2050 obtained with an energy system optimisation model of Ecuador (TIMES-EC), which has used the changes of hydropower availability factors to capture the impact that different climate change scenarios could have on the least-cost configuration of the power sector and overall energy system.

4.2 LEAST-COST ADAPTATION FOR THE ECUADORIAN POWER SYSTEM

The second research question of this thesis is: *"How does hydropower output variations due to climate change impact the long-term least-cost power system development pathway?"*[3]

To answer this question, the availability factors obtained in the previous section were used to characterise hydropower in a TIMES energy system model for the Republic of Ecuador (TIMES-EC) with particular detail of the power sector, as was explained in Section 3.2.4 on page 119.

The energy supply optimisation calculations with TMES-EC were run for three policy cases (Boost Hydropower, Constrain Hydropower and Environment Priority) and four climate change long-term scenarios (Dry, NoCC, Mean and Wet), as detailed in Section 3.2.10 on page 151. This section will compare the results for power generation,

3 The results of this section have been published in Carvajal PE, Li FGN, Soria R, et al (2019), Large Hydropower, Decarbonisation and Climate Change Uncertainty: Modelling Power Sector Pathways for Ecuador. *Energy Strategy Reviews*

system costs and GHG emissions. Therefore showing the effect of policy cases and changes in water variability for hydropower generation in the context of the least-cost evolution pathway of the electricity system.

4.2.1 *Power system configuration*

TIMES-EC finds that installed electricity generation capacity for all assessed scenarios increases by 15 – 18 GW and electricity generation by 65 – 74 TWh/y by 2050, which amounts to over a threefold increase compared to current levels, as can be seen in Figure 4.12 on the next page. The configuration of the power sector for 2017 and 2050 will depend according to the policy case and climate scenario outcomes that may transpire. Whereas the current portfolio is a hydrothermal one dominated by large scale hydropower generation, the model shows that the future could hold a number of different options, as can be seen Figure 4.13 on the following page. Notice that the scenarios which use the NoCC and the Mean climate assumptions give very similar results when compared across all three sets of policy assumptions. Therefore, the discussion below will mostly focus on the results of using the Wet and Dry climate scenarios, compared with the NoCC scenario.

The Boost Hydropower policy case under any climate scenario implies the deployment of large fractions of hydropower ROR and DAM in the electricity mix. The Constrain Hydropower and Environment Priority policy cases are more conservative for hydropower deployment, reflecting the limitations that were forced to limit its deployment. It is also seen that the scenarios employ different proportions of ROR and DAM type plants, which can be seen in Figure 4.14 on page 201 where the capacity range of each technology in 2050 has been depicted. This reflects the fact that these two types of technologies were modelled differently in terms of price, potential, size and availability.

Under the followed methodological approach and assumptions, the results suggest that in general, under all climate change scenarios, similar proportions of ROR and DAM capacity is suggested by TIMES-EC (this will change once risk is introduced in the model, as will be presented in following Section 4.3 on page 220). This potentially draws into question whether or not the Ecuadorian Government's focus on very large DAM projects, e.g. Santiago-G8 (2,400 MW) CELEC, 2017 – is the best approach from a cost-optimal strategy, especially considering that natural gas, hydro ROR or other renewables such as biomass and geothermal power could also be used to provide base load generation. Only in the Boost Hydropower policy case with a Wet climate scenario, does the model deploy almost close to 12 GW of hydropower by 2050. All other scenarios

Figure 4.12: Projected total electricity capacity (top) and generation in Ecuador at scenario level

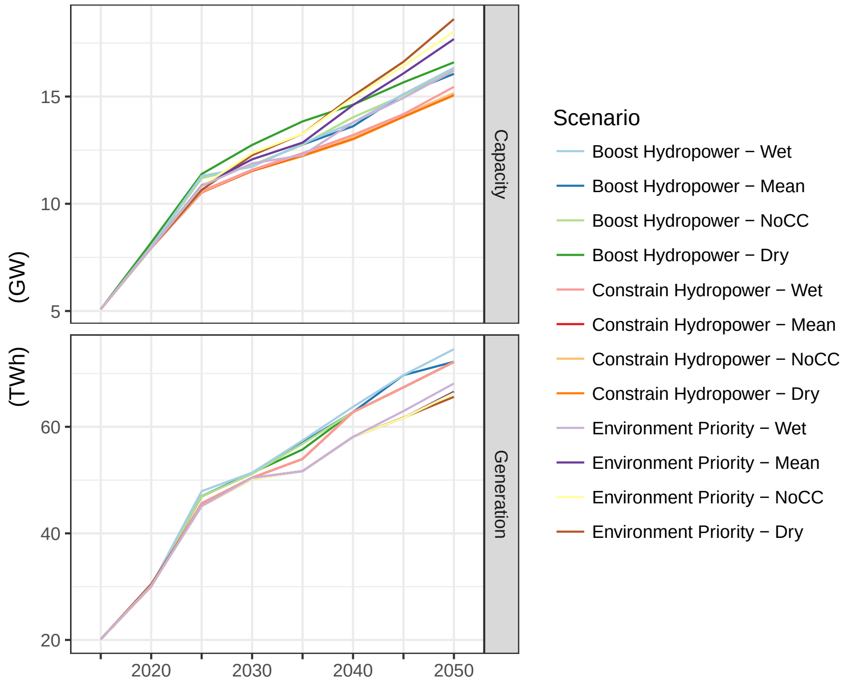


Figure 4.13: Installed capacity (top) and electricity generation in the power sector in 2017 and 2050.

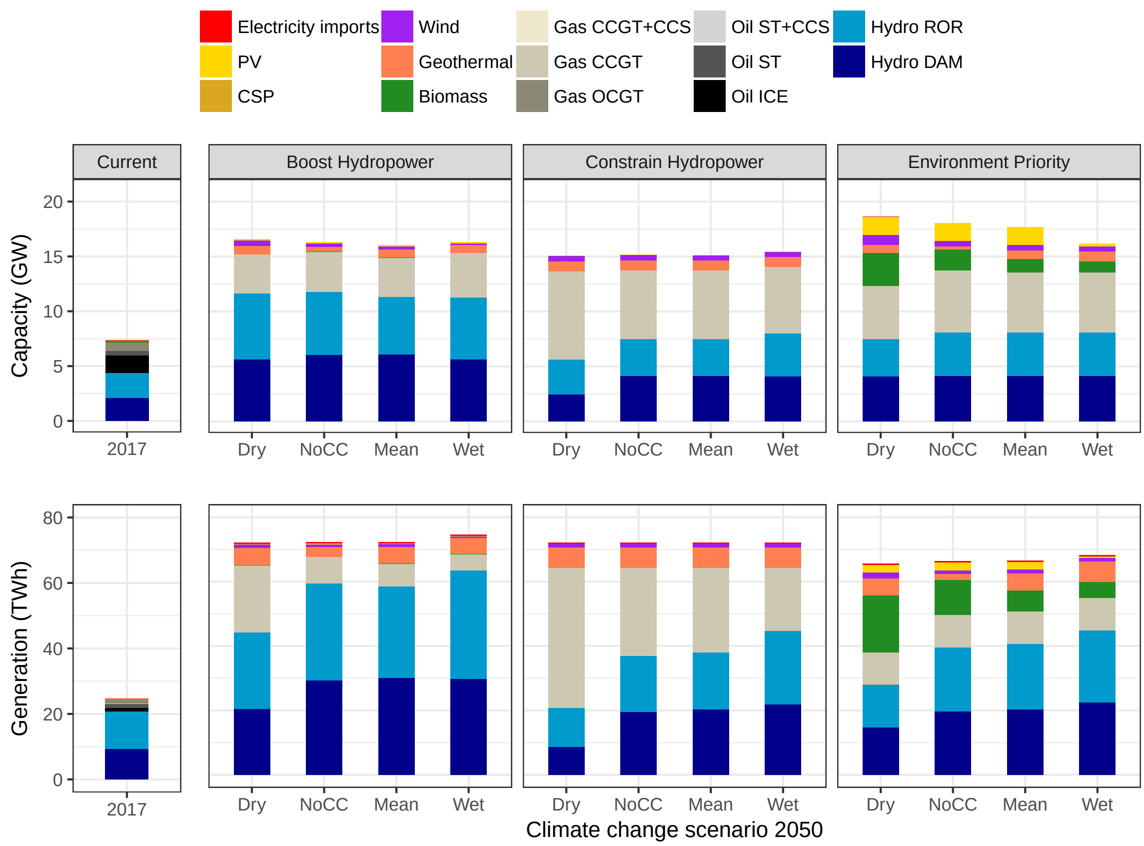
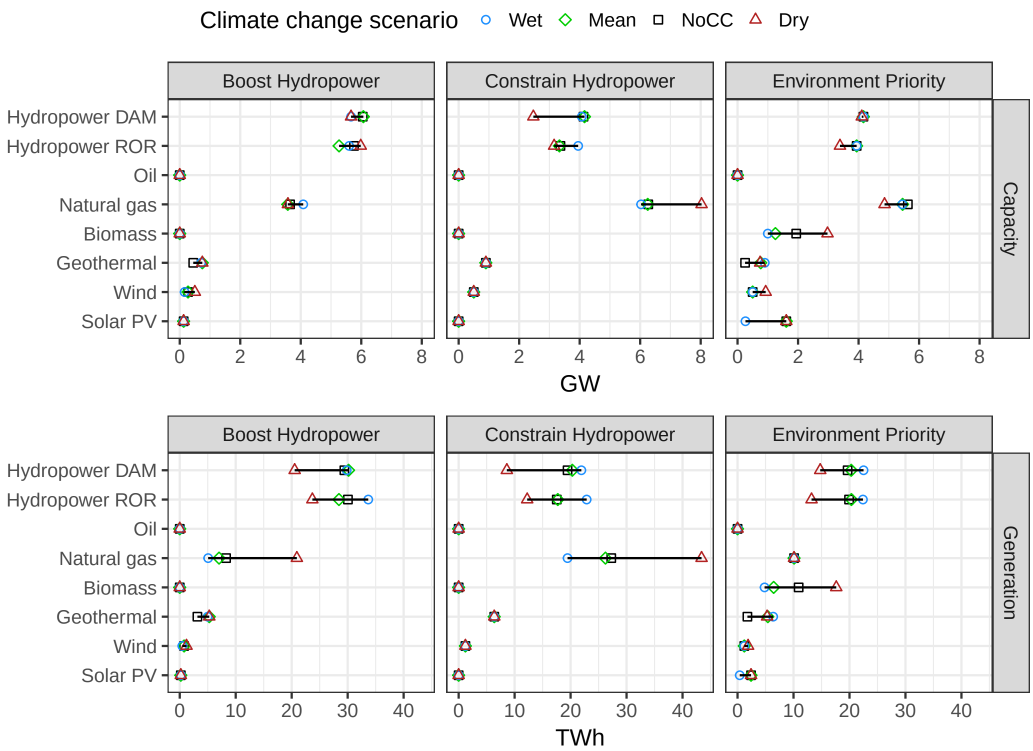


Figure 4.14: Installed capacity (top) and electricity generation (bottom) by technology type, policy case and climate change scenario by 2050



show levels below the threshold of the remaining assessed potential of 13 GW (see Figure 4.13 on the preceding page).

The deployment path of hydropower capacity and generation per type, climate change scenario and policy case can be seen in Figure 4.17 on page 204. Notice that the model only deploys large shares of hydropower DAM (~6 GW) when it is forced in the Boost Hydropower policy case. In comparison, the Constrain Hydropower and Environment priority scenarios show lower and similar installed capacity development pathways for hydropower that vary little depending on the climate occurrence, except for the Constrain Hydropower policy case with Dry climate scenario in which the model chooses not to deploy Hydropower DAM. Hydropower generation levels change according to climate scenario, generating less for Dry occurrences, however similar values for the Wet, Mean and NoCC climate scenario, corroborating the fact that increases in precipitation do not necessarily translate into windfall production of hydropower energy, but decreases can signify significant losses.

As was mentioned in the Introduction chapter on page 3, Ecuador's main energy policy was to achieve a 90% share of hydropower generation in the power matrix by 2021 and continue efforts to maintain a high share of hydropower generation. Across the climate change scenarios, the share of total electricity which can be generated by hydropower varies significantly by 2050 (29 – 86%) and changes throughout the modelling

Figure 4.15: Installed capacity by policy case and climate change scenarios in Ecuador for 2017–2050

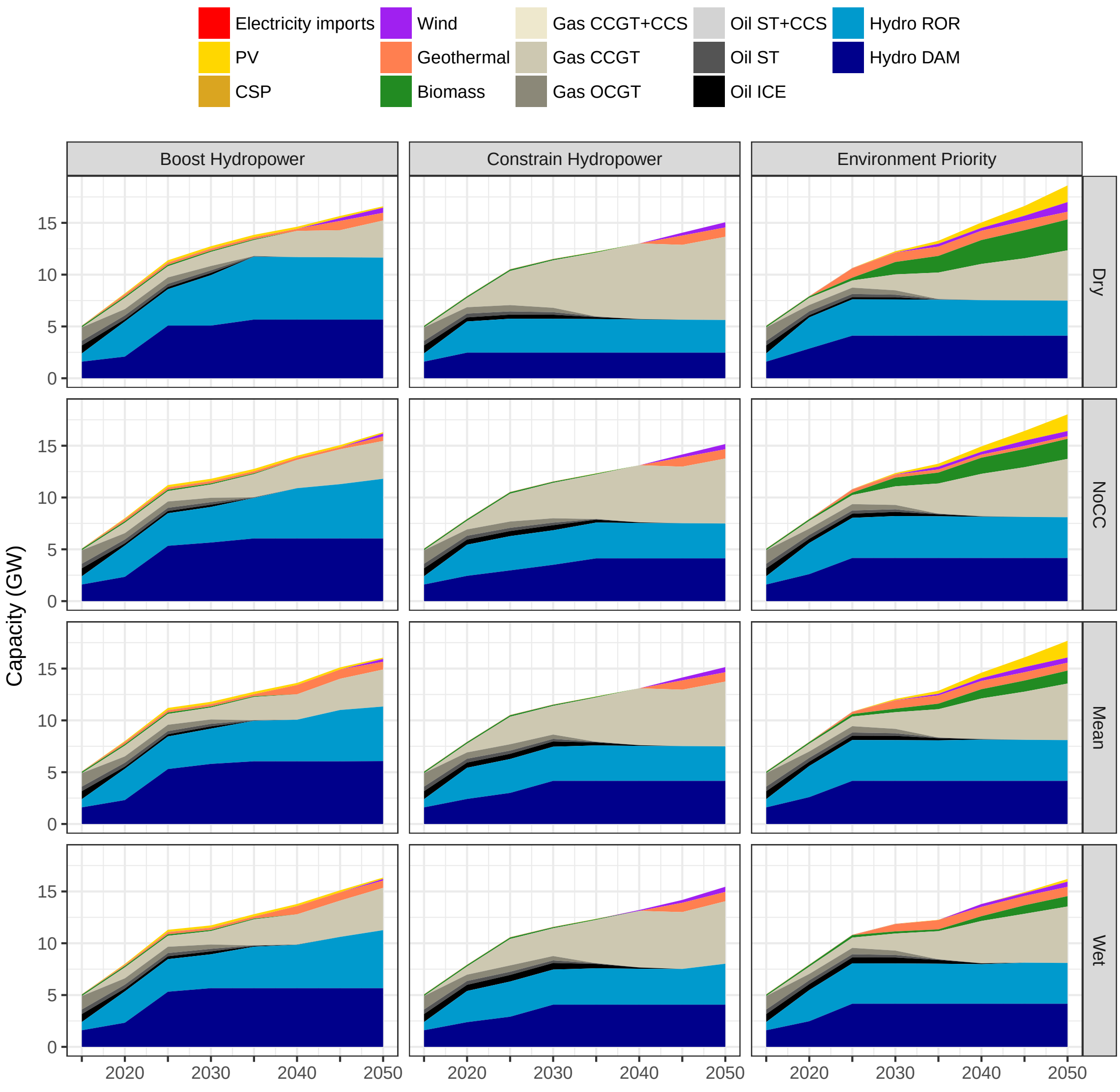


Figure 4.16: Electricity generation by policy case and climate change scenarios in Ecuador for 2017–2050

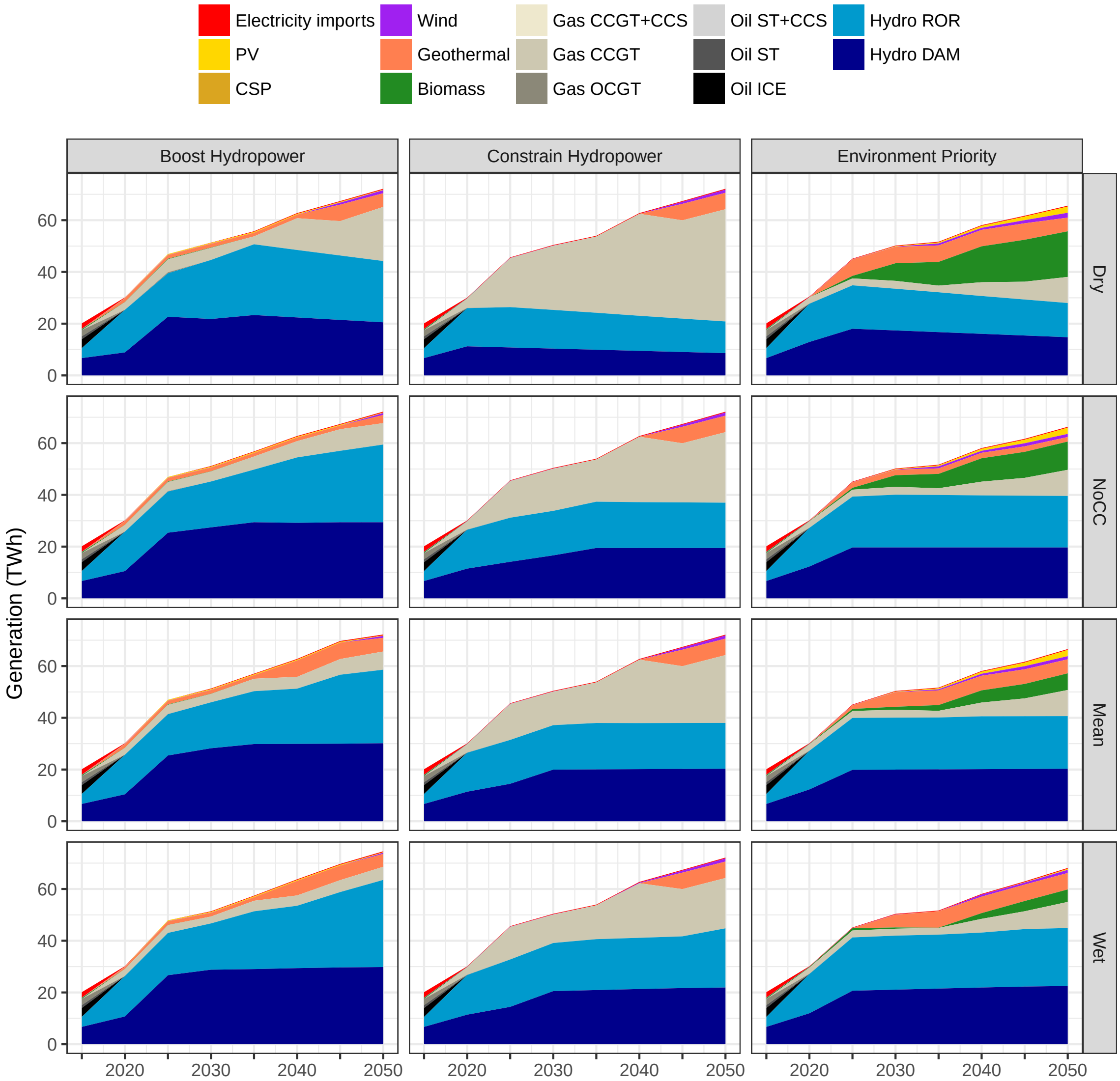
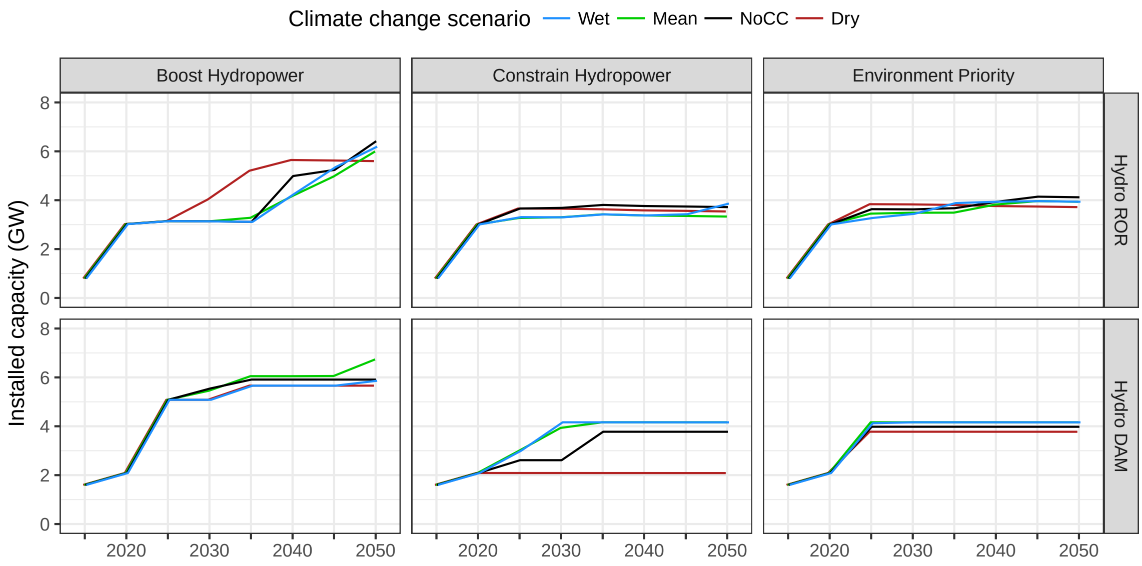


Figure 4.17: Hydropower installed capacity pert type, climate change scenario and policy for 2017–2050



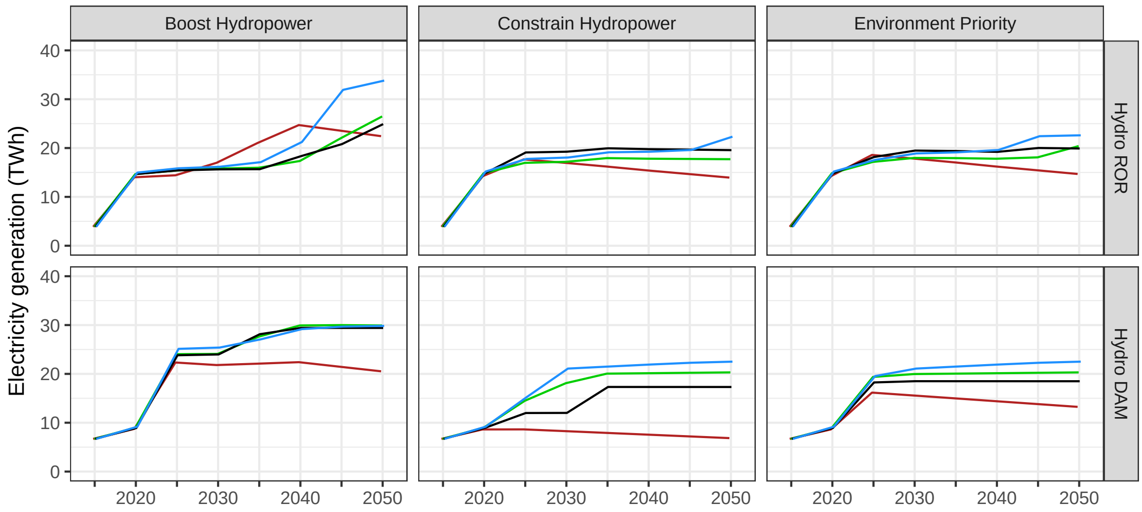


Figure 4.18: Share of hydropower in the generation matrix for the 2017–2050 period per policy case and climate change scenario

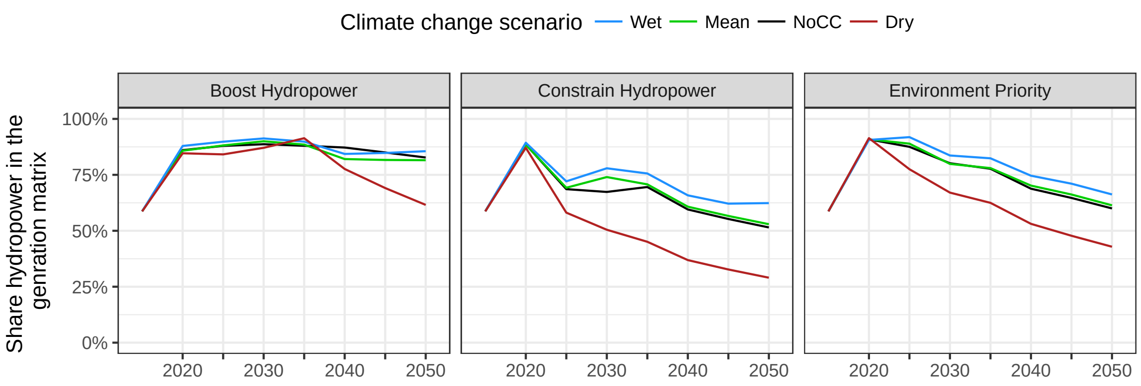


Table 4.6: Main results from the TIMES-EC model for installed capacity and annual average hydropower generation in 2050

	Policy case	2017		Climate scenario in 2050					
			NoCC	Dry	Δ	Mean	Δ	Wet	Δ
(GW)	Boost Hydropower	5.1	11.8	11.6	-1%	11.3	-4%	11.3	-5%
	Constrain Hydropower	-	7.5	5.6	-25%	7.5	0%	8.0	7%
	Environment priority	-	8.1	7.5	-8%	8.1	0%	8.1	0%
(TWh)	Boost Hydropower	24.5	59.5	44.2	-25%	58.6	-1%	63.5	7%
	Constrain Hydropower	-	37.0	20.9	-44%	38.0	3%	44.8	21%
	Environment priority	-	39.6	28.0	-30%	40.7	3%	44.9	14%

Note: Δ is the difference in percent respect to the NoCC climate change scenario.

horizon, as shown in Figure 4.18 on the facing page. In the Boost Hydropower scenario, the share of electricity demand that can be supplied by hydropower ranges from 62% up to 86% in 2050, which shows that hydropower can remain a major generation source even in the occurrence of a dry climate scenario, but not reaching the desired 90% threshold. In the Constrain Hydropower scenario the share of electricity demand that can be supplied by hydropower ranges from 29% up to 62% in 2050, which represents a negative offset of around -30% compared to the estimated range for the Boost Hydropower scenario. In the Environment Priority case, the share of electricity demand that could be supplied by hydropower is roughly between the Boost Hydropower and the Constrain Hydropower cases between 43% – 66%. Table 4.6 summaries the findings for year 2050, showing the variation of hydropower capacity and generation for all climate scenarios and policy cases. The next paragraphs will further detail findings for each policy case scenario and on electricity demand.

In this subsection, electricity portfolio configurations for a snapshot in 2050 have been assessed. For electricity installed capacity, generation and demand pathways for the entire modelling horizon 2017–2050 please see Figure 4.15 on page 202, Figure 4.16 on page 203 and Figure 4.22 on page 214, respectively.

4.2.1.1 *Boost Hydropower policy case*

Generally, it can be observed in Figure 4.13 on page 200 that the Boost Hydropower case results, which are intended to represent the Ecuadorian Government's intended policy trajectory in favour of hydropower until 2025, have the highest proportion of ROR and DAM hydropower capacity. However, once the fixed DAM capacity is installed until 2025, in line with the current policies stated in the PME (MEER, 2017a), TIMES-EC then installs only ROR hydropower for the remainder of the time horizon (see Figure 4.17 on page 204).

Even though this policy case is dominated by hydropower, its installed capacity configuration does not change greatly depending on climate change scenario, as as can be seen in Figure 4.14 on page 201. The configuration of the system remains a hydrothermal one with the majority of the capacity corresponding to hydropower and complemented mainly by gas-fired thermoelectricity. Despite the configuration of installed capacity not varying much, generation share varies greatly depending on climate change scenario. Interestingly, in the Dry scenario (where there is a significant drop in runoff), reduced hydropower generation is supplemented with a significant uptake of gas-fired generation from 10 TWh in the Wet and NoCC scenario to 25 TWh in the Dry scenario.

Natural gas technologies are the ones buffering hydropower variability in the Boost Hydropower scenario, even though its installed capacity does not vary much irrespective of climate scenario (3.5 – 5 GW). This finding means that even in the occurrence of an optimistic NoCC or Wet scenario, thermal capacity must still be deployed as a backup for the dry season months (October to January), regardless of the amount of hydropower capacity. The model prefers to install gas-fired capacity and have it be idle during most part of the year, rather than deploying more hydropower DAM with storage capacity.

Given that hydropower with its low marginal cost is forced in this scenario, other non-hydro renewables are displaced and there are only small shares of geothermal, wind and PV that are deployed. However, an important share of geothermal generation is present ranging from 1 to 5 TWh, unfortunately its capacity is capped at 0.9 GW according to resource inventory. The model does not deploy further oil generation capacity or biomass generation, CSP, or any fossil technology with CCS.

The Boost Hydropower policy case shows the highest capacity and generation values when compared to the the Constrain Hydropower and Environment Priority cases across all climate scenarios (see Table 4.6 on the preceding page). Hydropower installed capacity values is around 11 GW for all climate scenarios, but electricity generation ranges significantly between 44.2 – 63.5 TWh in 2050 depending on climate scenario. Generation in the Wet scenario is 6.8% higher when compared to the NoCC case (59.5 TWh), but falls considerably by -25.6% lower for a Dry scenario.

4.2.1.2 *Constrain Hydropower policy case*

The Constrain Hydropower policy case assumption prohibits the investment in additional large hydropower projects, representing a future where environmental and social concerns limit their construction. This policy case is characterised by the highest level of investment (6 – 8 GW) and electricity generation with gas-fired thermal plants when compared to the Boost Hydropower and Environment Priority cases. Although all climate scenarios under the Constrain Hydropower policy case make use of some hydropower resources of small and medium capacity (~7.5 GW), gas-fired thermoelectricity is a dispatchable electricity generation technology that is less sensitive to climatic variations, and one that appears to effectively fill in the gap created by the restriction of large hydropower capacity in this scenario (see Figure 4.13 on page 200).

The Constrain Hydropower case shows the potential for the leading role that natural gas generation might come to play in Ecuador in the event that large hydropower development is not possible and a dry climate scenario comes to pass (up to 45 TWh in the Dry scenario, Figure 4.14 on page 201). While not explicitly modelled in our analysis, it is also worth highlighting that higher annual temperatures driven by climate change could well have effects on plant cooling systems required for thermal electricity generation (Sathaye et al., 2012).

In this policy case, TIMES-EC suggests to deploy geothermal capacity at its maximum potential (0.9 GW) and wind capacity at double (0.5 GW) of what was deployed in the Boost Hydropower policy case (see Figure 4.14, top). PV, CSP or biomass generation are not selected at all in this scenario, which are totally displaced by highly flexible gas-fired plants. Hydropower total capacity in the Constrain Hydropower policy is roughly two-thirds of what was suggested for the Boost Hydropower policy and hydropower generation share only reaches half in the NoCC and Wet scenarios (37 – 48 TWh) but falls down to 20 TWh in the Dry scenario, which is the lowest share of hydropower in any of the assessed scenarios (see Table 4.6 on page 205). TIMES-EC conclusively shows that if large hydropower (>450 MW) is restricted, and there are no economic incentives or polices to enforce the deployment of non-hydro renewables, the least-cost expansion of the power sector is with gas-fired CCGT.

4.2.1.3 *Environment Priority policy case*

This scenario restricts the future deployment of large hydropower projects at the same time as constraining cumulative emissions for the 2017–2050 period at the level of those expected for the Boost Hydropower and NoCC scenario (53 GtonCO_2e), which reflects Ecuador's current position on energy system decarbonisation. This policy scenario generally shows the highest total cumulative installed capacity (up to 18 GW) out of all scenarios, as can be seen in Figure 4.12 on page 200. Compared to the Boost Hydropower and the Constrain Hydropower cases, the TIMES-EC model compensates for the shortfall in electricity from large hydropower in the Environment Priority case by deploying a significant capacity of biomass electricity (1 – 3 GW) and solar PV (0.5 – 2 GW) capacity (see Figure 4.13 on page 200).

Given the larger shares of intermittent generation capacity from weather-dependant renewables, the model also installs thermal generation capacity in a proportional fashion in order to provide back-up to the system. Which is the typical paradox around large deployment of intermittent renewables – *the more climate friendly intermittent renewables, the more flexible fossil fuel thermal back up* (Schaeffer et al., 2012). Gas-fired electricity capacity in the Environment Priority scenarios (5 – 6 GW) reaches levels lower than the Constrain Hydropower policy case but higher than those of the Boost Hydropower scenario. However, given that emissions are capped, a part of the thermal back-up has to be with biomass. Generation from biomass (mainly through direct biomass combustion plants with CEST) is the source of electricity generation that the model appears to rely the most to buffer the possible negative variations in future hydropower output. This can be seen very clearly in the Environment Priority Dry scenario where electricity generated from direct biomass combustion plant almost equates to the output of hydropower (~20 TWh/y). Even though emissions level is capped in this policy scenario, no CCS technologies are detected in the results, despite being available for the model to choose.

Even though PV has a considerable level of installed capacity in these scenarios, it only reaches a maximum share of 3% of electricity generated in 2050 (3 TWh/y). Taking a closer look at solar technologies, it is verified that PV technology, both at the utility scale and at the level of distributed generation is the preferred choice in the model. Concentrating Solar Power (CSP) type plants with several hours of thermal energy storage systems are available in the model but are still not found to be economical to deploy even in the most critical Dry scenario. Wind power resources above 7.5 m/s at 80 m are deployed while geothermal potential is also installed at levels similar to those found in the Boost Hydropower scenario (0.9 GW). The model still considers small and medium ROR hydropower plant deployment as the least-cost source of electricity for mitigating emissions with levels similar to the Constrain Hydropower scenarios (~ 8 GW).

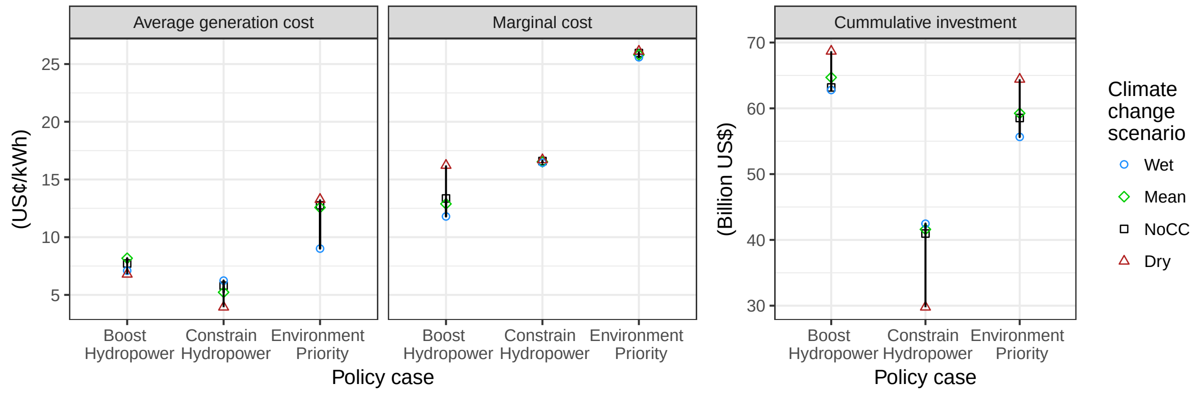
This scenario unveils the potential importance of biomass generation for future deep decarbonisation policy in Ecuador. Given that wind and geothermal potential are almost completely tapped in 2050, that solar PV may also reach its technical potential due to intermittency issues, and that concentrating solar power and natural gas with CCS appear to be prohibitively expensive to deploy, the main alternative left in the model for a low-carbon scenario that has constraints on large hydropower plants appears to be biomass generation. Biomass power could also have its own issues that merit further investigation. It should be highlighted that the biomass resource itself could be exposed to climate vulnerabilities due to the effects of higher temperatures and extreme hydrological conditions, such as both floods and droughts. The use of biomass for energy generation also brings with it a broader set of social and environmental concerns, that should be investigated in future research efforts.

4.2.2 *Power system costs*

The analysis using TIMES-EC finds that future policy decisions and variations in hydropower production associated with climate change have an uncertain impact on future electricity system costs, namely average generation costs, marginal generation costs and cumulative investment costs, which are presented in Figure 4.19 and Table 4.7 on the following page. Regarding average generation cost, the Constrain Hydropower policy case is the cheapest (4 – 6 US¢/kWh). Although as discussed ahead, the Constrain Hydropower case may bring with it significant implications for future GHG emissions and energy security. The most expensive option from an average generation cost perspective is the Environment Priority case (9 – 13 US¢/kWh), with a range that almost doubles the one of the Constrain Hydropower case. The Boost Hydropower case has a middle-of-the-road average generation cost compared to the other policy cases (6 – 8 US¢/kWh).

Average generation cost results indicate that the optimal power expansion pathway from a least-cost perspective would be with a gas-fired dominated power matrix. However, these results consider a single trajectory for natural gas that considers current prices at 3 US$/Btu and 5 US$/Btu in 2050 according to the reference scenario of the US Energy Information Administration Outlook EIA (2017). This assumption of constant and low gas prices will be challenged in Section 4.3 on page 220 by considering the volatility that prices of natural gas could have. The Boost Hydropower scenario, although more expensive would somehow mean a more robust approach in terms of price, given that it is only slightly higher than the Constrain Hydropower costs and would rely less on gas. The idea that large hydropower infrastructure offers the possibility of low average generation costs will likewise be challenged in Section 4.3 on page 220 by introducing the uncertainty of large hydropower infrastructure capital cost. The Environment Priority scenario stands out for having very high average generation costs, given the fact that more expensive non-hydro renewables have to be deployed to comply with emission constraints and also overcome the restriction to deploy large hydropower. However, in the occurrence of a Wet scenario, the Environment Priority

Figure 4.19: Average long-term electricity generation cost, average marginal cost and cumulative investment for policy cases and climate change scenarios, for the period 2017–2050.



Note: Figures are in US_{2015}

Table 4.7: System cost summary for policy case and climate change scenario in Ecuador for 2017–2050

			Climate scenario in 2050					
	Policy case	NoCC	Dry	Δ	Mean	Δ	Wet	Δ
Average cost (US¢/kWh)	Boost Hydropower	7.7	6.7	-13%	8.1	5%	7.0	-9%
	Constrain Hydropower	5.8	3.9	-33%	5.2	-10%	6.2	7%
	Environment priority	12.7	13.2	4%	12.5	-2%	9.0	-29%
Marginal cost (US¢/kWh)	Boost Hydropower	13.3	16.3	23%	12.8	-4%	11.7	-12%
	Constrain Hydropower	16.5	16.7	1%	16.5	0%	16.4	-1%
	Environment priority	25.9	26.1	1%	25.8	0%	25.5	-2%
Cumulative investment (bill. US$)	Boost Hydropower	63.1	68.6	9%	64.6	2%	62.7	-1%
	Constrain Hydropower	40.9	29.7	-27%	41.6	2%	42.4	4%
	Environment priority	58.5	64.4	10%	59.2	1%	55.6	-5%

Note: Δ is the difference in percent respect to the NoCC climate change scenario.

cost falls to the levels of the Boost Hydropower scenario; meaning that if there is water availability in the future, an intensive hydropower policy could have the same costs as a more diversified generation portfolio with larger shares of non-hydro renewables and only small and medium hydropower.

While the average generation cost is important for investors, the marginal cost is the metric that will likely affect government policies the most (such as subsidies for clean energy), as consumers are charged based on marginal costs. Average marginal costs for the modelling horizon can be seen in Figure 4.19 (middle panel). It is observed that marginal cost is largely impacted by the climate change scenarios only in the Boost Hydropower policy case (12 – 16 US¢/kWh), in which part of the peak demand could be covered with cheap hydropower, particularly in the occurrence of a Wet or NoCC scenario. The marginal costs of the boost scenario are affected by the constraint that forces hydropower into the system – this constraint also has a price and it lowers the marginal cost of electricity (similar to feed in tariffs for solar PV and wind generation lowers the marginal cost of electricity market prices). Fluctuations in the marginal price are then a consequence of the volume of low-cost hydropower electricity pushed into the market. The cost of this forcing is reflected clearly in the cumulative investment cost shown in Figure 4.19 on the facing page (right panel).

The marginal cost achieved under the Constrain Hydropower scenarios set, although slightly more expensive than the Boost Hydropower scenarios, stands out for its narrow range of variation under different climate conditions (all instances 16 US¢/kWh) and accordingly appears to have a low level of climate vulnerability. In this gas dominated power matrix, flexible gas-fired generation will be the technology of preference to cover peak demands although some might still be covered by DAM hydropower. The marginal costs found under the Environment Priority case have also a narrow uncertainty band respect to climate scenario (see Figure 4.19, middle panel), but it is very high reflecting the fact that expensive biomass generation is being used to cover demand peaks (look at Figure 4.13 on page 200 to see the share of biomass generation in the Environment Priority policy case).

The cumulative investment costs for the 2017–2050 period are also presented in Figure 4.19 (right). The Boost Hydropower policy case is found to generally be the most capital-intensive option (around US$ 65 billion), the Constrain Hydropower case is generally the cheapest option (around US$ 35 billion), and the Environment Priority case appears to represent an intermediate point between the two (around US$ 60 billion). The Boost Hydropower policy case combined with the Dry climate change scenario is found to be the most capital-intensive pathways of all with total investment costs close to US$ 70 billion. This is because this occurrence would account not only for building new large hydropower plants but also a requirement to install further thermal capacity to supply electricity as a result of the risk of generation shortfalls due to dry conditions.

The Constrain Hydropower policy case combined with a Dry climate pathway presents the least capital-intensive option (US$ 30 billion), as it is dominated by natural gas technologies with lower investment costs compared to hydropower and other renewables. However, it should be noted that this scenario does little to keep Ecuador on a path towards a low carbon future and has high emissions, as well as having implications for energy security due to the requirement for future natural gas imports, as discussed ahead. The Environment Priority policy case is the middle case – less capital intensive than the Boost Hydropower approach while also offering a generation matrix that is capable of maintaining low emissions consistent with Ecuador's current NDC.

4.2.3 *Electricity and final energy demand*

In line with the expected socio-economic development for Ecuador in the period 2017 to 2050, end-use energy demand increases between 58 – 68 TWh by 2050 as the projections shown in Figure 4.20 on the facing page. Electricity demand grows accordingly and varies depending on the electricity prices resulting from different policy cases and climate scenarios. By 2050, electricity demand is highest in the Boost Hydropower police cases (~65 TWh) and lowest in the Environment Priority policy cases (~60TWh). The feature of being able to capture the reaction of the demand side to changes on the availability of supply is one of the key advantages of using an integrated energy system model, such as TIMES.

In general, the residential, industrial and strategic industry sectors are the largest consumers of electricity by 2050, as can be seen in Figure 4.21 on the next page. By 2050, power demand in the Boost Hydropower policy case is 65 TWh, except for the Wet climate scenario in which total power demand grows to 68 TWh. In this case, the abundance of hydropower generation with low marginal costs incentives energy service demands in the residential sector to switch from fossil fuel to electricity. Particularly shifting water heating and cooking from LPG to electricity, which is the only possible fuel switch in the residential sector.

The Constrain Hydropower shows demand in 2050 to be 65 TWh and there is no differences for climate scenarios (see Figure 4.21 on the facing page). Most probably this is due to higher marginal costs of a system with larger shares of gas-fired generation that does not offer incentives to switch energy services to electric appliances. In comparison, power demand of the Environment Priority policy case is lower at ~60 TWh by 2050 and does show changes depending on climate scenario. In this case, the industrial sector seems to react to higher marginal and average generation costs. The availability of runoff causes the industrial sector to slightly use more electricity in direct heat demands in the Wet climate scenario, than in the Dry climate scenario.

It is emphasised that while demand shifts and fuel switching according to electricity (or energy) prices have been captured in this study, this in reality will depend on the price elasticity of demand and the policies that are implemented to allow such changes. Demand changes can be driven by energy price changes, but are mainly consequence of energy efficiency improvements, structural changes to low carbon or zero carbon fuel/-technologies, and reduction in energy-service demands itself (useful energy) (Li and Pye, 2018). This research is focused on the least-cost configuration of a hydrothermal power system and therefore the analysis of how demand my evolve due to climate change

Figure 4.20: Projected total electricity demand in Ecuador at scenario level

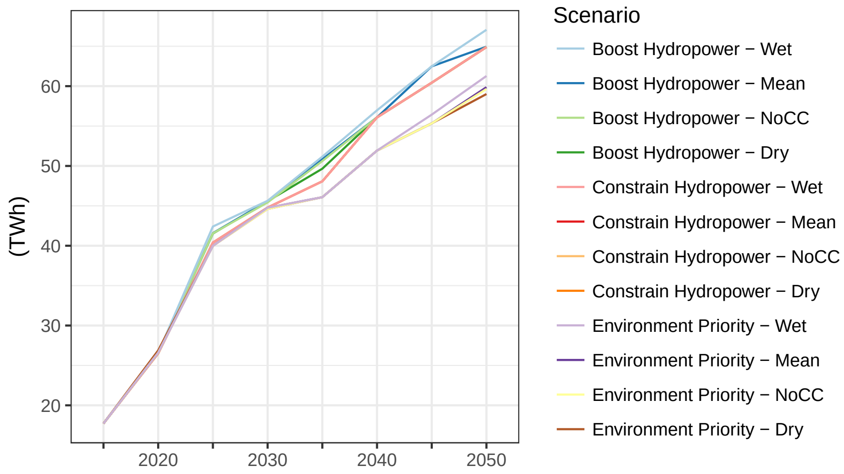


Figure 4.21: Electricity demand per economic sectors in 2017 and 2050

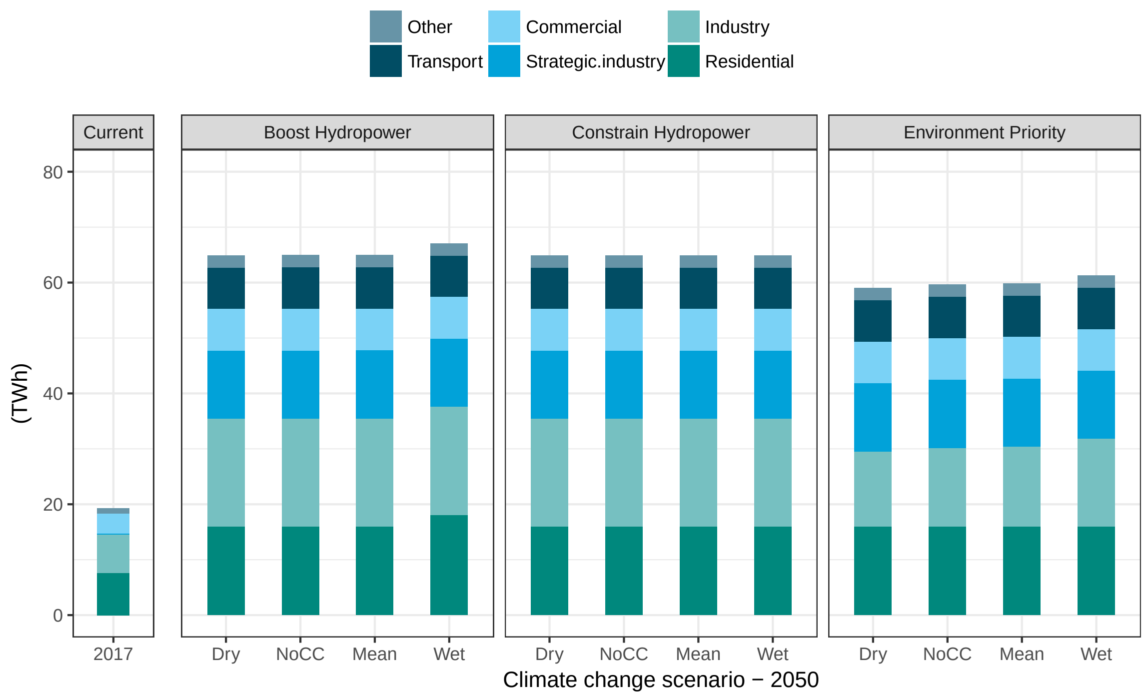
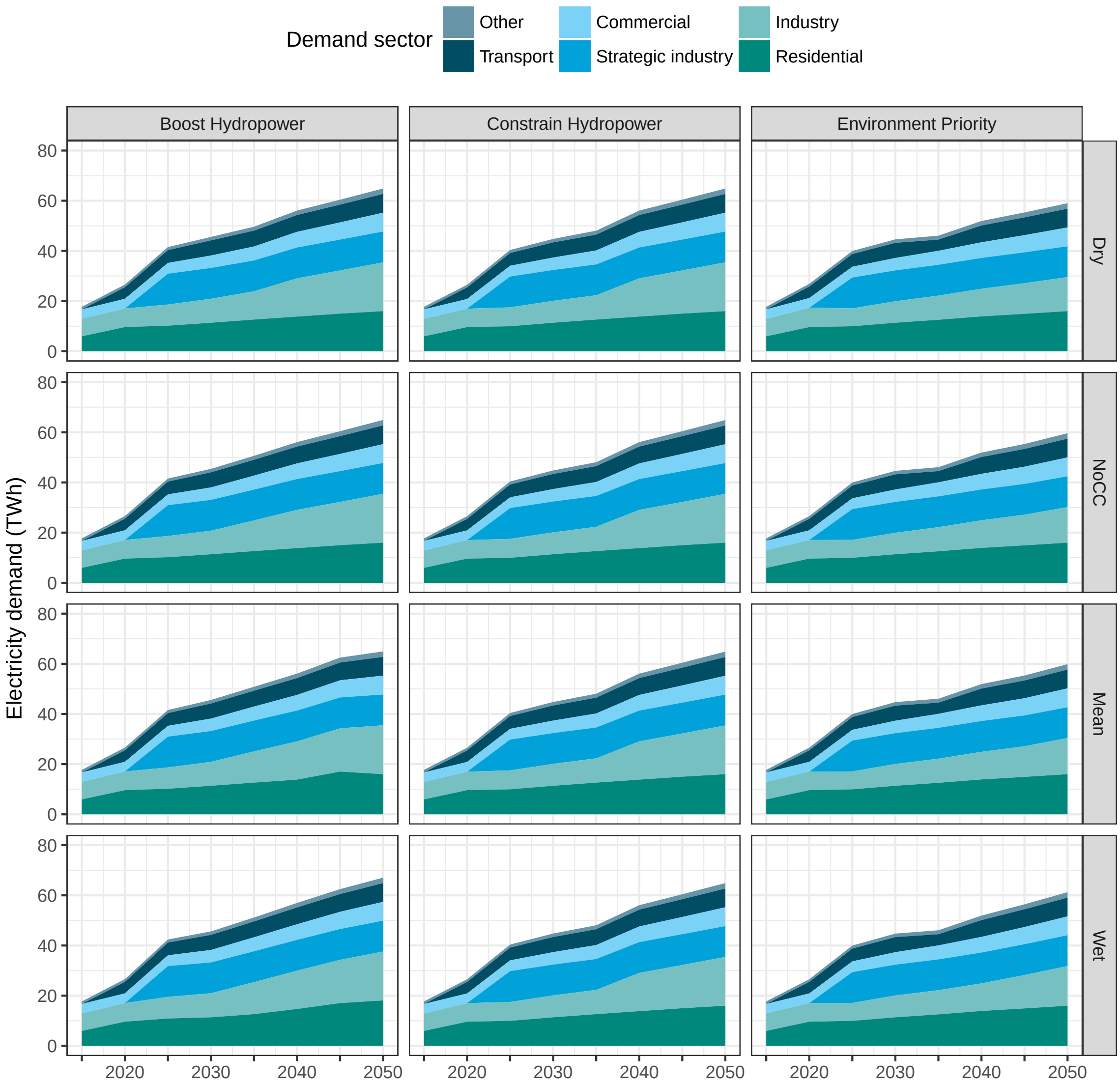


Figure 4.22: Electricity demand per economic sector in Ecuador for 2017–2050



impacts and polices requires further research with modelling technics and assumptions that can capture consumer behaviour more accurately, such as with the elastic demand version of TIMES (Kesicki and Anandarajah, 2011).

Beyond electricity demand, the energy system model also allows to assess the whole energy system in terms of its final energy demand. Figure 4.23 on the next page shows final demand by sector and fuel, which in 2050 reaches almost 1,200 PJ, compared to 574 PJ in 2017. By 2050, the lion's share of final energy demand corresponds to the transport sector, followed by industry, which together consume around 70% of total energy demand. The residential and commercial sectors see smaller increases due to population growth stagnation and the implementation of energy efficiency policies, particularly moving away from LPG to electricity for cooking. In terms of fuel, petroleum products and gas dominate over 75% of final energy demand in 2050, the remaining being supplied by electricity and a small share of biomass (see bottom panel of Figure 4.23). It must be noted that the differences registered in the power sector due to policy case or climate change scenarios translate only to small variations in final energy demand, this is mainly because the electricity sector is projected to be only a small part of the energy system by 2050 and that the largest consumers, which are the industrial and transport sectors, mainly use fossil fuels to operate.

In addition, it can be seen in Figure 4.23 on the following page (bottom) that by 2050 gas imports play an important role not only for the power sector, but for the industrial sector. Ecuador has only a relatively small level of proven natural gas reserves (10.9 billion m^3) (OPEC, 2017) and there is not any infrastructure built or planned that would allow the import of gas. Therefore the country would likely depend on foreign imports of LNG, creating an energy security issue that leaves the country vulnerable to shortages in the event that LNG import contracts cannot be secured in a timely fashion or in the event that sufficient on-shore or even floating storage regasification units (FSRU) are not built in due time. Energy security can also be negatively impacted due to the economic impacts due to the volatility of international energy markets.

Opening the Ecuadorian energy matrix to natural gas would need political will and significant investment, and a lock-in to natural gas might also be created in the power sector if non-hydro renewables fail to deploy, as was shown in the Constrain Hydropower scenario (see Figure 4.13 on page 200). If the country fails to introduce natural gas into the matrix, the needed base load generation would need to operate with liquid fuels, e.g. heavy and residual fuel oil, as has currently been occurring until now in Ecuador.

Figure 4.23: Final energy demand by sector and fuel in Ecuador by climate change scenarios and policy case in 2017 and 2050

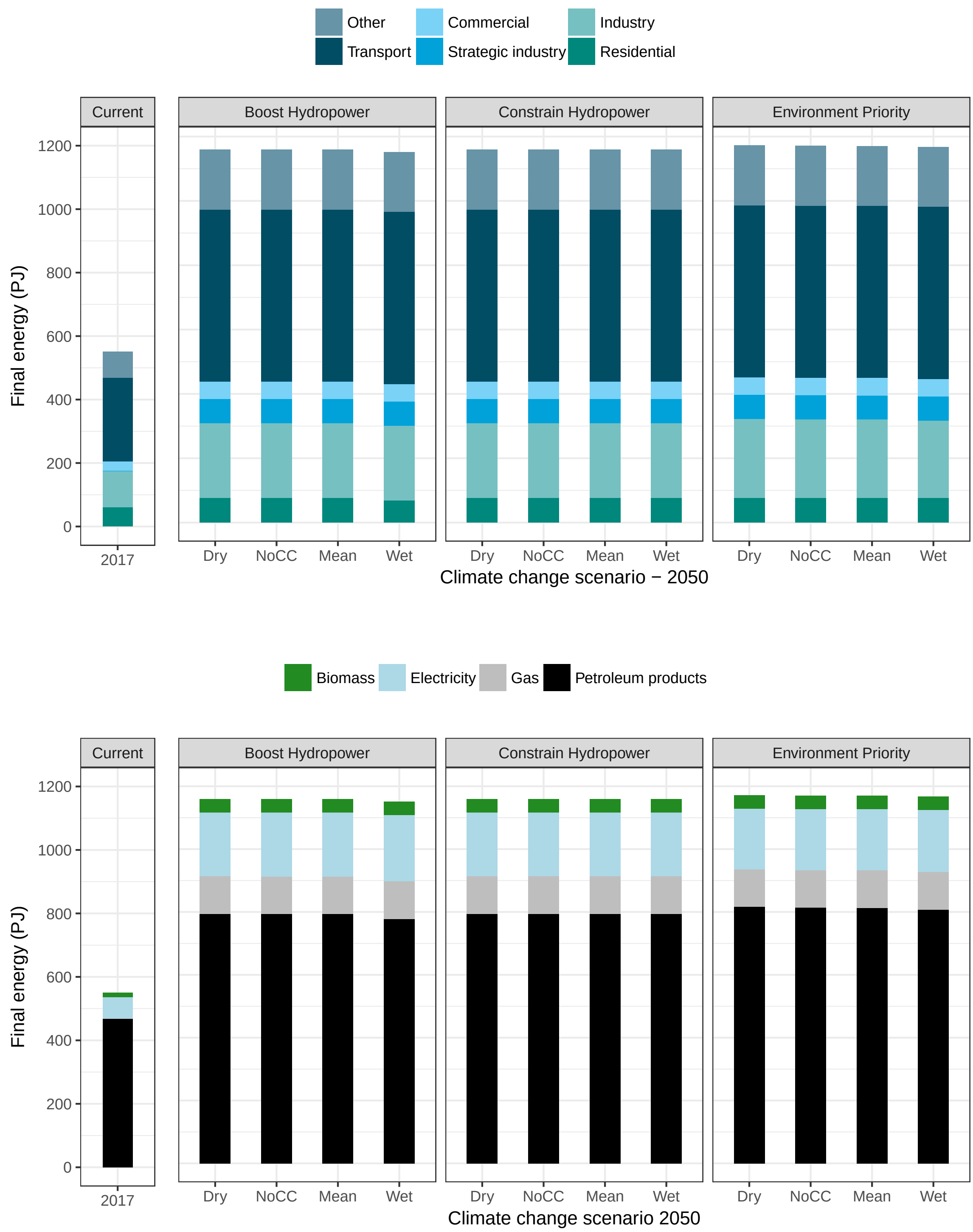
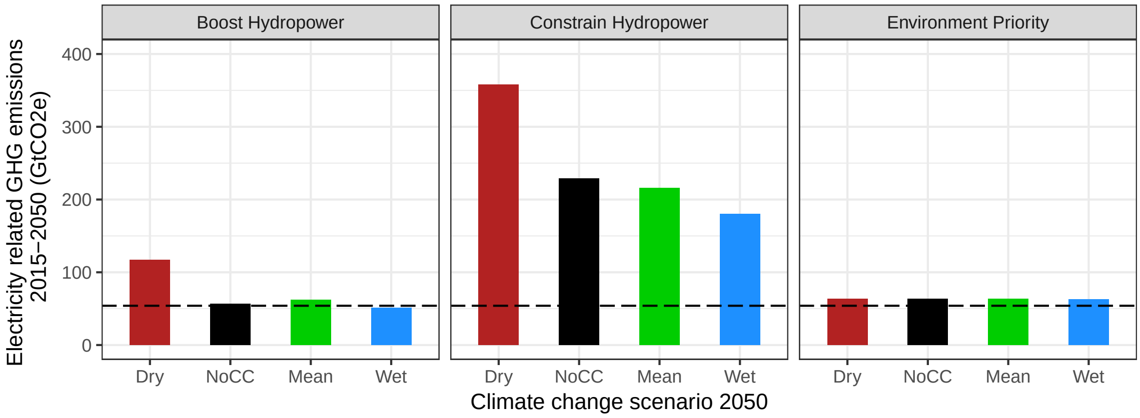


Figure 4.24: Cumulative electricity related GHG emissions for the period 2017–2050 per policy case and climate change scenario.



Note: The dotted line represents Ecuador's NDC emission level (53 GtonCO_2e).

It is noticed that climate change and policy cases for the deployment of hydropower only have a slight influence on final energy. However, it can be seen that Dry scenarios require more energy than Wet scenarios. In comparison, policy case impacts mainly the balance between oil products and electricity, particularly detected in the Environment Priority case.

4.2.4 *Electricity related GHG emissions*

Figure 4.24 shows cumulative electricity-related GHG emissions for the period 2017-2050 for all modelled scenarios. The emission level of the Boost Hydropower policy case and NoCC climate scenario is considered in this analysis as the expected value associated with the Ecuadorian NDC (53 GtonCO_2e). It can be seen that under the Boost Hydropower policy case set, the impact of climate variation on emissions is small, although there is a doubling in emissions under Dry conditions (100 GtonCO_2e) and a slight fall under Wet conditions (48 GtonCO_2e).

The Constrain Hydropower policy case, where large hydropower is prohibited, implies large increases in emissions as compared to the Boost Hydropower case. The most critical case is in the event of a dry scenario where future climate change decreases run-off availability in Ecuador, and where the government does not wish to (or is unable to) pursue large hydropower projects. In this case electricity related GHG emissions reach 350 GtonCO_2e, representing almost a seven-fold increase compared to the level implied in the current Ecuadorian NDC. Even when future climate variations result in a wet scenario, emissions are almost four times larger (175 GtonCO_2e) than the NDC. In general the Constrain Hydropower policy case causes a four-fold increase compared to the Boost Hydropower policy case.

Overall, the model results indicate that it may become difficult to prevent emissions from energy production increasing over time on a cost-optimal pathway without hydropower. This poses a trade-off between the social and environmental issues found at the local level, and the efforts to mitigate GHG emissions at the regional and global levels. As described earlier, an alternative set of pathways for maintaining emissions at the implied NDC level without large-scale hydropower is explored – namely, the Environment Priority policy case. However, this approach comes at a cost, as discussed previously.

4.2.5 *Summary*

This subsection has provided an assessment on the impact that different scenarios of climate change and power sector policy cases can have on Ecuador's long-term energy system. Results show that by 2050, hydropower will remain as one of the most cost-effective and low emission technologies in the Ecuadorian power sector. However, constraints on deployment and uncertainty around climate change impacts could hinder its ability to contribute to supply electricity demand, the fulfilment of NDC targets and maintain low power system costs. Across the climate change scenarios and policy cases, the share of total electricity demand which can be supplied by hydropower varies significantly (29 – 86%), as can be seen in Figure 4.18 on page 204.

Selected key outcomes of this subsection are summarised below (while all key findings are restated in the conclusion of this thesis in Chapter 6 on page 271):

- Based on the assumptions considered in TIMES-EC (see Section 3.2 on page 110) and demand projections based on the Shared Socioeconomic Pathway 2 (SSP2), total installed electricity generation capacity in Ecuador could increase by 15 – 18 GW by 2050, which amounts up to a threefold increase compared to current levels (7.5 GW in 2017). Whereas the current portfolio is a hydrothermal one dominated by large scale hydropower generation, the model shows that the future could hold a number of different options according to the policy case and climate scenario outcomes that may transpire. Electricity generation will need to increase by 70 – 78 TWh/y by 2050, which is up to a fourfold increase compared to current levels (24.5 TWh in 2017). This can be seen in Figure 4.13 on page 200.
- Extensive deployment of hydropower only occurs when large-scale hydropower potential in the Amazon can be tapped and is forced to enter the power system

(Boost Hydropower policy case in TIMES-EC). In this case, around 12 GW of hydropower would be installed by 2050 and other non-hydro renewables would be prevented from entering the system. However, even with large hydropower capacity installed, significant shares of gas-fired generation must be deployed to withstand the dry October to January season. This can be seen in Figure 4.14 on page 201.

- Restricting the deployment of large hydropower has a potential lock-in for gas-fired generating technologies, if non-hydro renewables fail to enter the system (Constrain Hydropower policy case). Restricting the deployment of large hydropower combined with the occurrence of a dry climate scenario could make gas-fired generation the main source of electricity by 2050 (> 70%), as seen in Figure 4.14 on page 201. This has implications for emissions – cumulative electricity related GHG emissions for the 2017–2050 period could increase five to seven-fold compared to the level implied in the current Ecuadorian NDC (53 GtonCO_2e), as seen in Figure 4.24 on page 217. In addition, a gas-fired power matrix can impact energy security. Given Ecuador's small natural gas resources, the Ecuadorian energy market would need to build new infrastructure and rely on foreign imports of LNG.

- Ecuador can achieve its NDC without the need of deploying large hydropower capacity, by deploying larges shares of biomass generation and small and medium hydropower (Environment Priority policy case). Wind, geothermal and PV also contribute more in this policy case, but biomass's role combined with small/medium sized hydropower is key to achieve the NDC when both emissions and large hydro deployment are capped (see Figure 4.13 on page 200). However this solution doubles system costs and increases marginal cost considerably depending on the price of biomass resources and technology, as can be seen in Figure 4.19 on page 210.

- Results show that hedging strategies for Ecuador include the shift away from gas-fired thermal generation and the uptake of non-hydro renewable energy. Table 4.8 on the following page shows a summary of the trade-offs found amongst the policy cases explored in this subsection, namely regarding the configuration of the power sector, its risk exposure to climate change, costs and GHG emission levels, as well as the key issues for security of supply in each scenario.

Finally, it should be emphasised that the optimisation with TIMES-EC was made for a given set of technical-economic characteristics that can change over time. Therefore,

Table 4.8: Trade-offs between risks, costs and emissions for policy case scenarios for the Ecuadorian power sector in 2050

	Policy case		
	Boost Hydropower	Constrain Hydropower	Environment Priority
Top technologies	ROR, DAM, Gas	Gas, ROR, DAM	ROR, DAM, Biomass
Risk to climate	High	Low	Low
Risk soc./env. issues	High	Intermediate	Low
Generation cost	Intermediate	Low	High
Investment	High	Low	Intermediate
GHG emissions	Low	High	Low
Security of supply	Good only if precipitation behaves as the past or increases.	Good only if gas imports are secured.	Good only if biomass resource can be tapped and its vulnerability to climate change is low.

relative price changes and technological advances may change the optimal configuration of the power sector for the Ecuadorian energy system. For example, adaptation in a less energy-intensive scenario, e.g. with no strategic industries, would be configured differently and rely less on large deployment of hydropower. It should also be emphasised that the impacts to which the adaptation alternatives were directed are a function of the climate projections adopted and the hydrological and hydropower simulation modelling results. That is, the impacts and least-cost adaptation alternatives described here are subject to the uncertainties of global and regional climate models beyond energy system modelling uncertainties. The following subsection will challenge the idea of deterministic and constant techno-economic conditions for the long-term by assessing the impacts of introducing fossil fuel price uncertainty and capital cost overruns uncertainty of electricity infrastructure in TIMES-EC with a novel Portfolio Theory approach.

4.3 COST-RISK TRADE-OFF ASSESSMENT WITH PORTFOLIO THEORY

The third research question of this thesis is: *How does incorporating recurring uncertainties such as the volatility of fossil fuel prices and the capital cost of electricity infrastructure impact the investment portfolio for the power sector?*[4]

4 The results of this chapter have been published in: Carvajal PE, Anandarajah G, Mulugetta Y (2019), A portfolio theory approach to assessing uncertainties in power system planning - A case study for Ecuador. *Energy Economics* (Under review)

To answer this question, a financial Portfolio Theory approach was integrated into the energy system optimisation model TIMES-EC. The methodology, which has been detailed in Section 3.3 on page 159, assesses the recurring uncertainty of fossil fuel prices and investment cost of electricity generation infrastructure. In addition, given the significance of hydropower in Ecuador, climate change has also been considered in this analysis as an additional source of uncertainty which could impact the foreseen availability of runoff for hydropower generation.

This section will present the results in terms of the efficient frontier derived from the trade-off between cost and cost risk, as well as the configuration of electricity generation portfolios and the technologies that present robust long-term development pathways for the power sector.

4.3.1 *Long-term evolution of uncertain parameters*

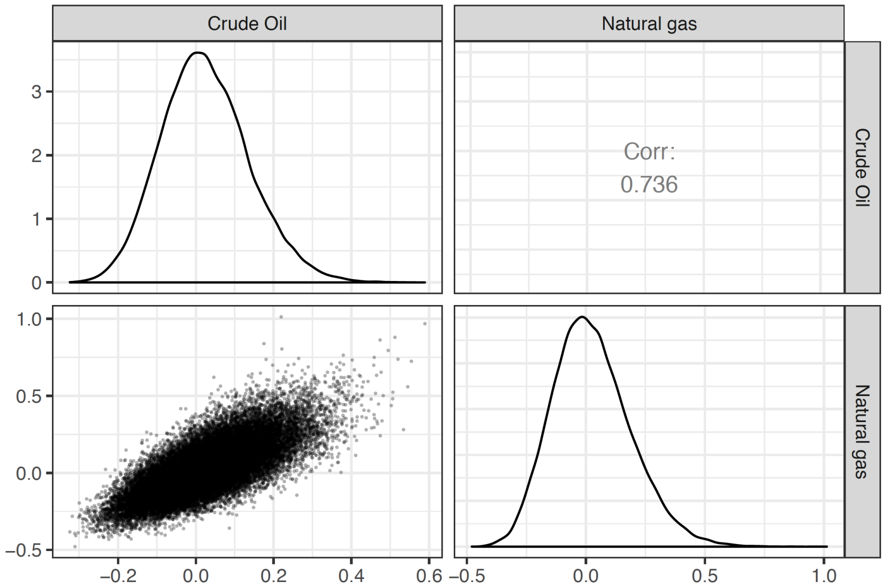
4.3.1.1 *Oil and natural gas prices*

To model alternative price paths of oil and gas, a Monte Carlo simulation approach governed by a multivariate Geometric Brownian Motion (GBM) price evolution model was used (as explained in Section 3.3.2 on page 167). Inputs for the GBM model were summarised in Table 3.24 on page 173 and correspond mainly to the probability distribution functions for crude oil and natural gas prices, as well as their corresponding historic correlation, which can be seen in Figure 4.25 on the following page.

Correlated Oil and gas prices were simulated for the period 2017–2050 through 1,000 Monte Carlo simulations, which can be seen in Figure 4.26 on page 223.[5] Notice that they do not follow a linear trend and rather follow different trajectories with seasons of high and low prices, and sudden shifts of price change (similar to the historic reality of prices for these commodities, see Figure 2.7 on page 85). Crude oil and natural gas prices have been simulated respecting their historic price correlation ($\rho = 0.74$) and evolve around their guided means during the modelling period – from 50 to 110 US$ per barrel for oil and from 3 to 5 US$ per million Btu for natural gas. Figure 4.27 on page 224 shows the correlated behaviour that has been captured between oil and gas prices for three selected simulated paths, they follow their price trends through time. This highlights the strength of portfolio theory for modelling recurring and correlated uncertainties, compared to a traditional scenario analysis and even to a stochastic approach, in which the number of

5 The results for modelling are presented up to 2050, although TIMES-EC runs until 2085 to avoid issues with end of the horizon investments. The simulated price paths beyond 2050 have been extrapolated until 2085.

Figure 4.25: Crude oil and natural gas prices correlation matrix and probability distribution functions for 1,000 Monte Carlo simulations



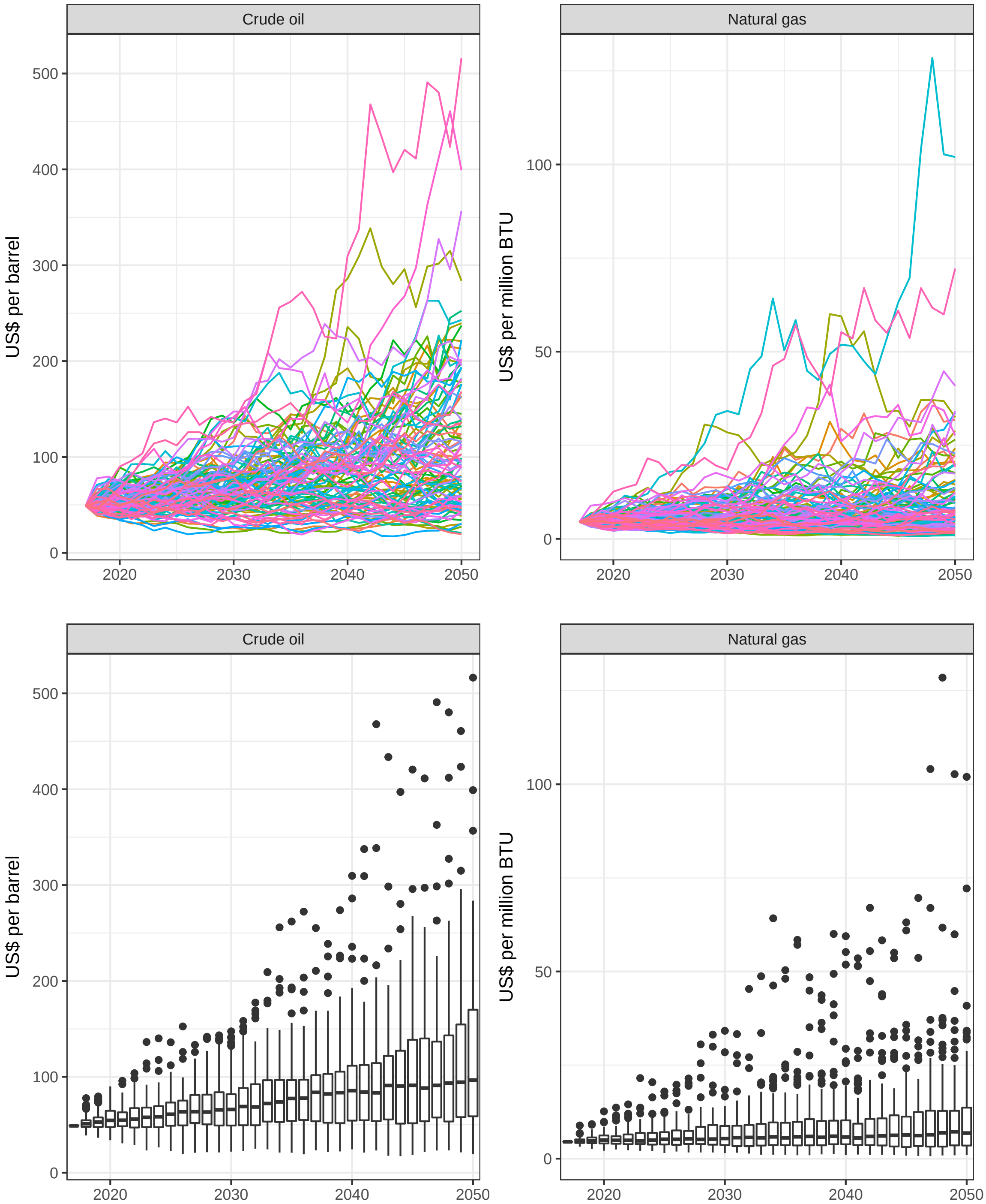
scenarios that can be incorporated is much lower because of computational restrictions (Usher and Strachan, 2012).

4.3.1.2 *Electricity infrastructure investment cost*

Investment costs paths of hydropower, thermal plants, solar facilities and wind farms were also modelled using 1,000 Monte Carlo simulations similar to that of oil and natural gas. Inputs for the GBM model were presented in Table 3.25 on page 174 and consist mainly on the probability distribution functions of cost overruns for electricity generation technologies. The probability distribution functions of infrastructure cost overruns can be seen in Figure 4.29 on page 225 (left panels), where mean cost overrun of hydropower infrastructure is significantly higher (70%) than for other technologies, as well as having a much greater spread and a long tail.

Once the probability distributions for different technologies were defined, investment cost trajectories were then generated for the period 2017–2050 through 1,000 Monte Carlo simulations. Selected simulated electricity infrastructure capital cost paths can be seen in Figure 4.29 on page 225 (right panels). Cost overruns are present for all technologies, with hydropower showing significant cost uncertainty compared to thermal power plants, wind farms or solar facilities (see different scales of y-axis). Notice that there is a reduction in the expected prices of PV and wind technology up to 2050 (respecting expected cost reductions BNEF, 2016), while hydroelectric and thermal plants

Figure 4.26: Selected price paths for crude oil and natural gas modelled with 1,000 Monte Carlo simulations. Absolute values (upper panel) and box and whiskers (lower panel).



Note: The boxplot compactly displays the distribution of a continuous variable. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 * IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Data beyond the end of the whiskers are called "outlying" points and are plotted individually.

Figure 4.27: Correlated price paths for crude oil and natural gas

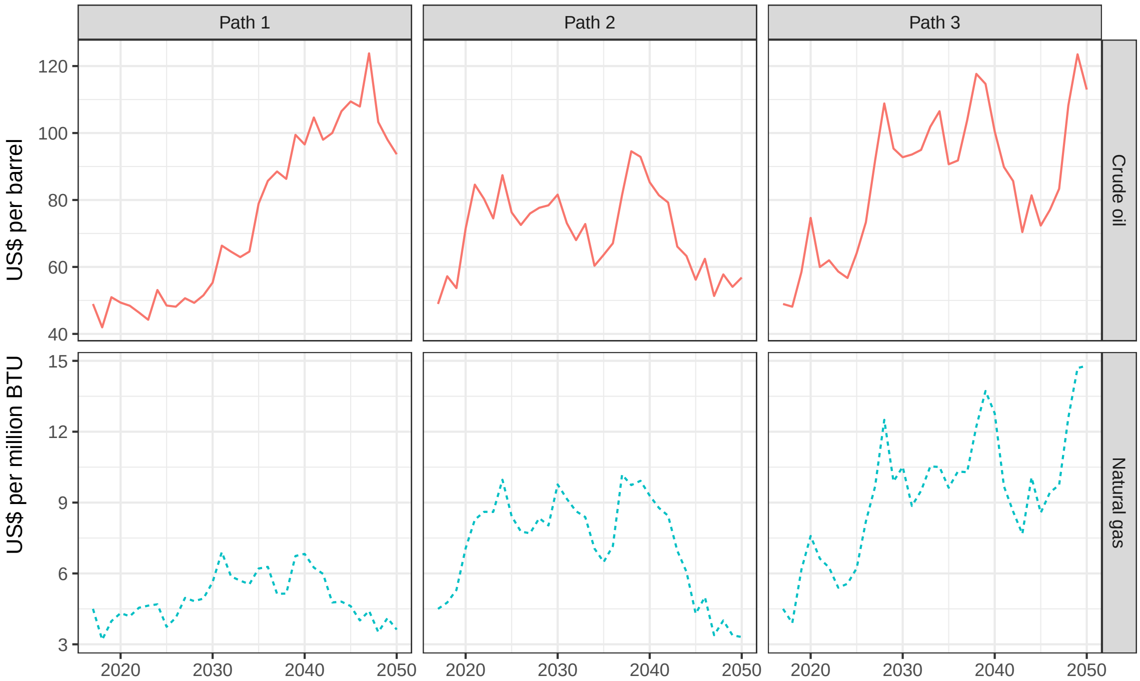
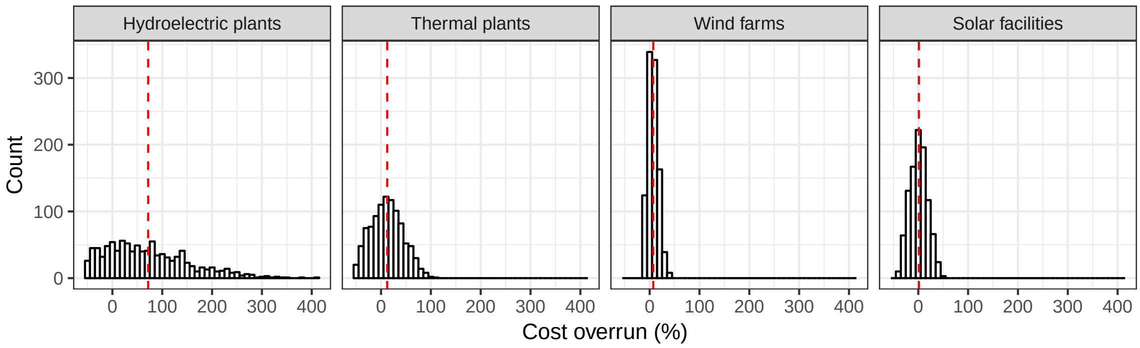


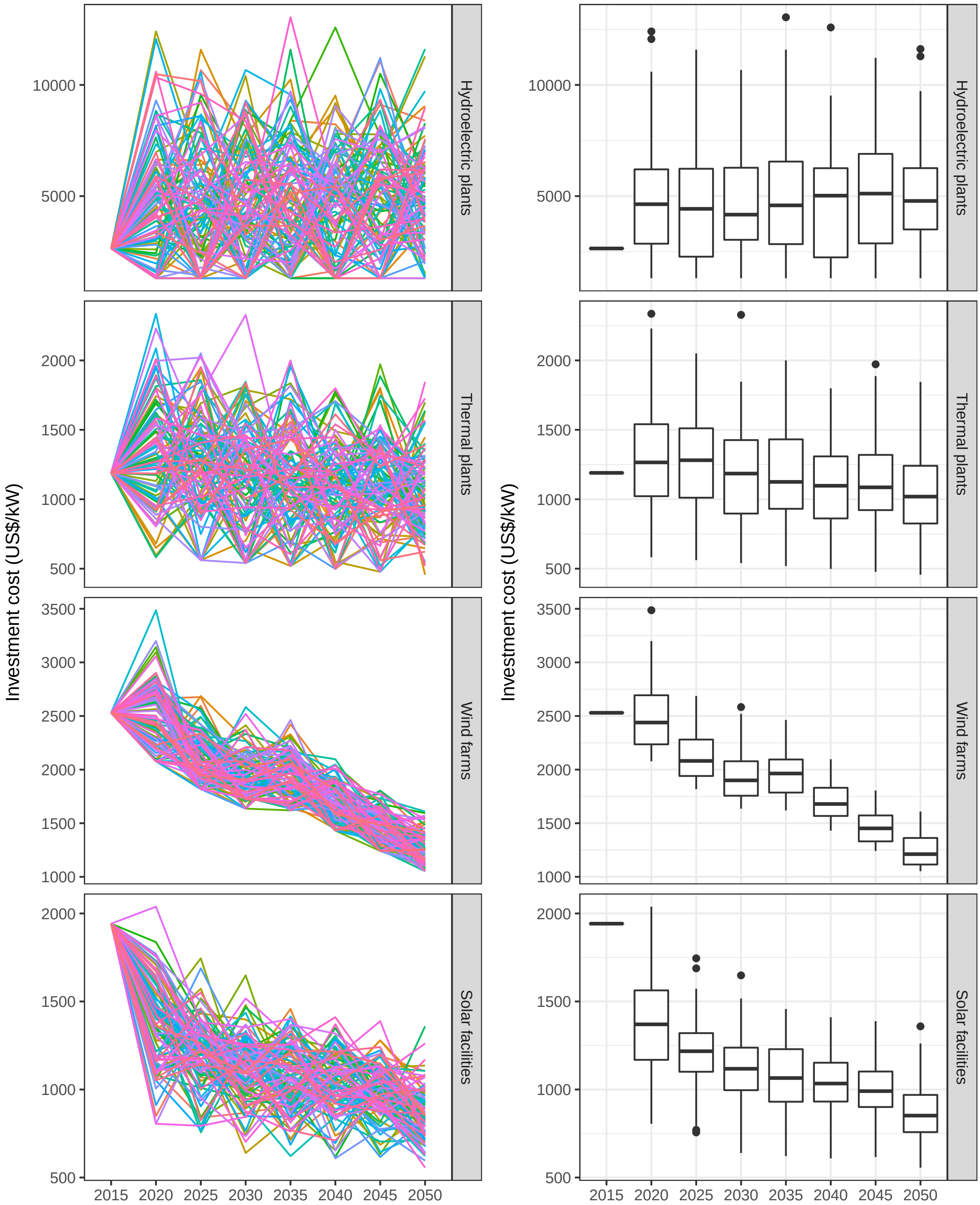
Figure 4.28: Cost overrun probability distribution functions for electricity generation technologies



are considered to have reached technological stagnation and their capital costs are not projected to reduce (Hirsch, 2003).

In contrast to the price paths simulated for oil and natural gas, the simulation of electricity infrastructure costs evolves within a range of maximum and minimum cost overrun deviation according to the sample of infrastructure cost overruns presented by Sovacool et al. (2014a) (see Table 3.25 on page 174). The 1,000 scenarios of fossil fuel prices and capital cost for power technologies for the 2017–2050 period were input to TIMES-EC and were taken into consideration by the model according to the methodology described in Section 3.3 on page 159.

Figure 4.29: Investment cost paths modelled with 1,000 Monte Carlo simulations.



Note: Red dashed line in the left panel shows the mean cost overrun. Notice different scale for y-axis in right panels. The boxplot (right panel) compactly displays the distribution of a continuous variable. The lower and upper hinges correspond to the first and third quartiles (the 25th and 75th percentiles). The upper whisker extends from the hinge to the largest value no further than 1.5 * IQR from the hinge (where IQR is the inter-quartile range, or distance between the first and third quartiles). The lower whisker extends from the hinge to the smallest value at most 1.5 * IQR of the hinge. Data beyond the end of the whiskers are called "outlying" points and are plotted individually.

4.3.2 *Power sector portfolio*

TIMES-EC was run for six levels of increasing risk level (from risk neutral to risk averse) and three scenarios of climate change (Dry, NoCC and Wet), as was detailed in Table 3.27 on page 176. The integration of the risk of fossil fuel prices and capital cost for infrastructure causes installed capacity to range between 15 – 23 GW and electricity generation to range between 72 – 83 TWh by 2050, as can be seen in Figure 4.30 on the facing page. Dry climate scenarios are seen to require larger installed capacity than NoCC and Wet climate scenarios, but generate less electricity than these two latter.

Figure 4.31 on the next page shows the installed capacity and electricity generation for 2017 and 2050, and illustrates the model's preferred options to reduce overall cost risk for each climate change scenario. In general, results show that as the level of risk moves from risk-neutral to risk-averse, the power system moves away from a generation portfolio with gas-fired generation and ROR hydropower, towards one with more DAM hydropower, geothermal, solar PV and wind. Hydropower maintains an important capacity share (>50%) for any scenario by 2050. Non-hydro renewables are therefore considered as a way of hedging against uncertainty, in particular solar PV and geothermal capacity in the occurrence of a Dry climate change scenario. The variation range of installed capacity and electricity generation can be seen more clearly in Figure 4.32 on page 228, in which technologies are depicted separately and risk level is shown by a gradient of colours – blue is risk averse while red is risk neutral.

Taking a look at the portfolio configuration in 2050 for the NoCC and Wet scenarios, it is seen that these results are somewhat similar (see Figure 4.31 on the next page). In these scenarios, total installed capacity falls as risk level increases driven my progressive reduction of ROR hydro. However, this is replaced by an increase in hydropower DAM, geothermal, PV and wind. The installed capacity of gas-fired electricity generation is maintained at fairly constant levels and reduces only slightly with the risk level. Biomass generation technology is only considered by the model for risk neutral levels in the Dry and NoCC scenario and is replaced by larger shares of geothermal and PV as risk level increases. No capacity additions of oil-fired generation are registered in any of the modelled scenarios, nor CCS technologies.

The increase of DAM hydro to reduce risk in the NoCC and Wet scenarios might seem counterintuitive, considering DAM hydro's higher cost and risk compared to other generating technologies. This is an interesting finding, which is explained by the fact that even though DAM hydro is more expensive than ROR hydro and they are considered to have similar cost risk profiles, the model will prefer DAM over ROR because DAM

Figure 4.30: Projected total electricity capacity (top) and generation in Ecuador at scenario level for Portfolio Theory in TIMES-EC

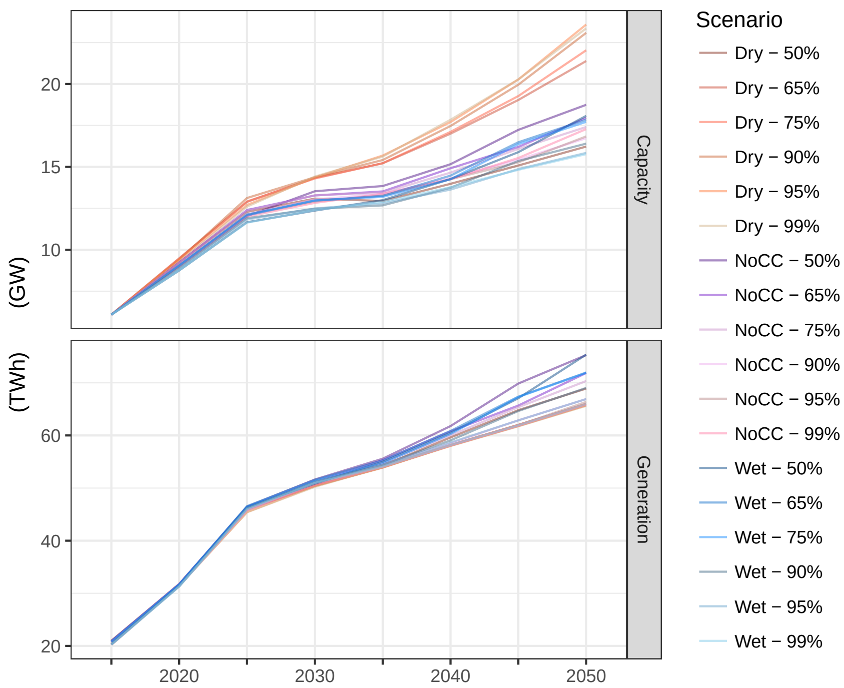


Figure 4.31: Installed electricity capacity and generation by 2050 per technology, risk aversion level and climate change scenario

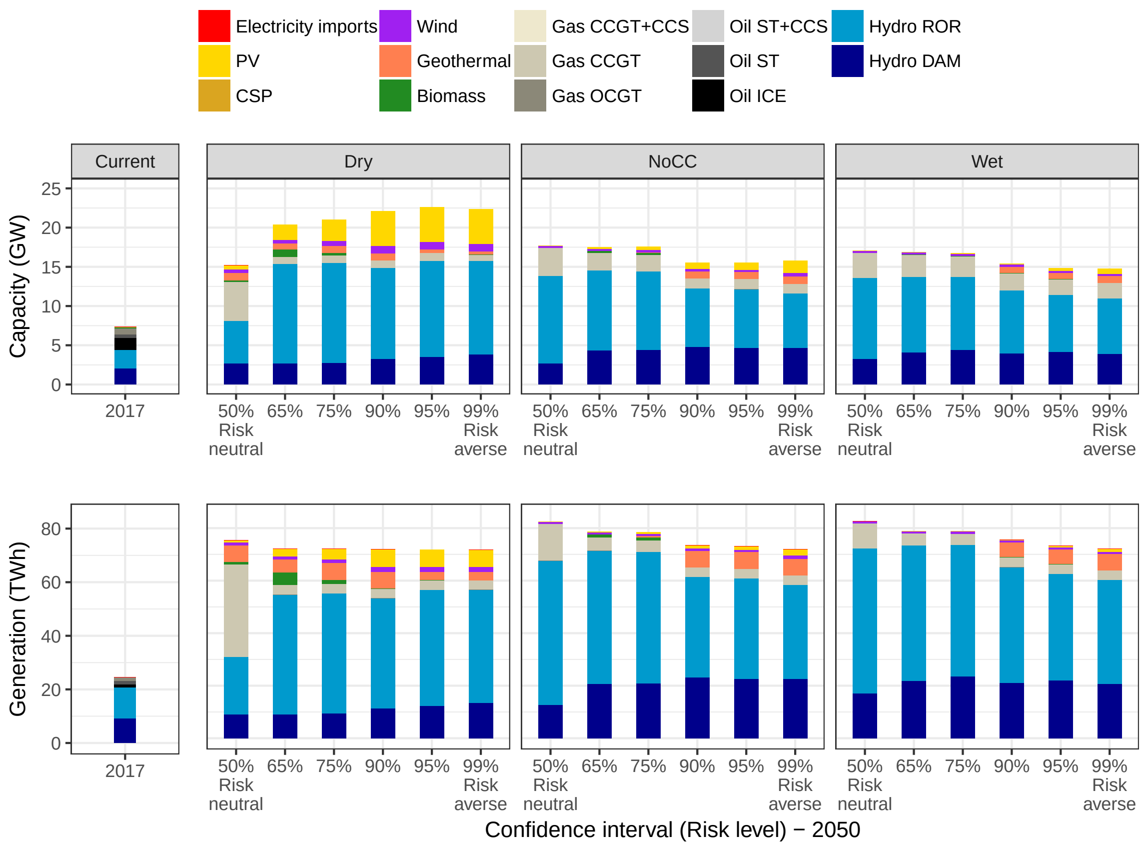
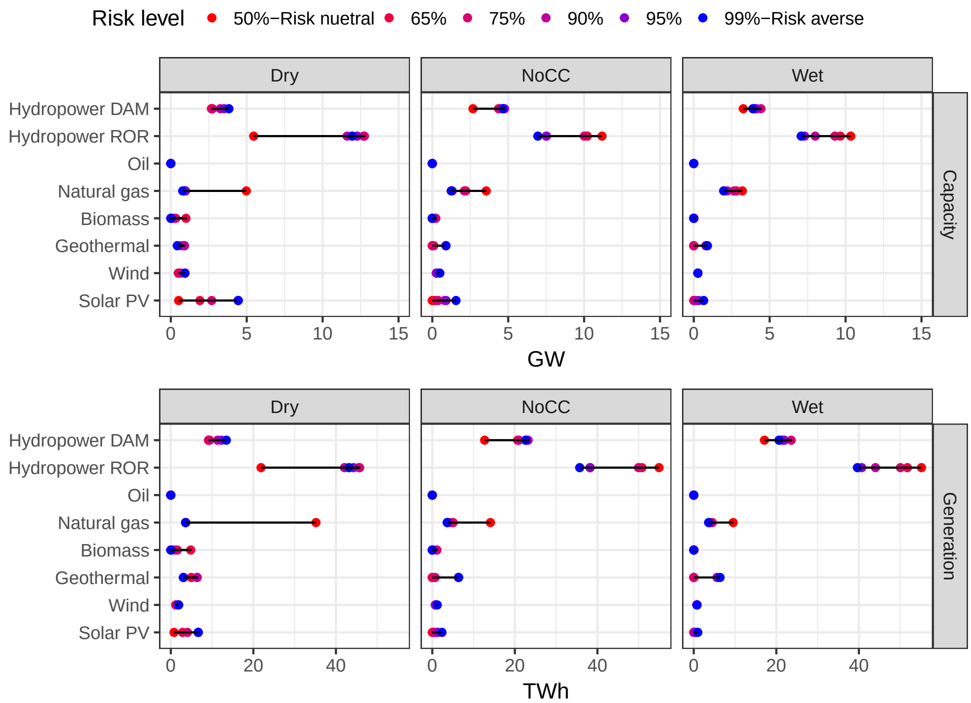


Figure 4.32: Installed capacity (top) and electricity generation (bottom) by technology type, policy case and climate change scenario by 2050



hydro has storage capabilities that can help to replace risky gas-fired backup necessary for an increased uptake of intermittent renewables (solar PV and wind). However notice that the replacing of hydro DAM with hydro ROR is not proportional (Figure 4.32) – roughly 1 GW of DAM replaces 2 GW of ROR. the deployment of intermittent PV and wind is also accompanied by corresponding capacities of geothermal energy which has been considered as firm capacity in the model. It is also noticed that despite the increasing level of risk of natural gas prices, the model maintains a consistent minimal share of natural gas capacity (~1 GW) for all risk levels.

The Dry climate scenario shows a different approach to power sector risk hedging by increasing total installed capacity, as when compared with the NoCC and Wet scenarios which show total capacity reductions. At the risk neutral level, the model chooses to have a power system with large shares of gas-fired thermal electricity, similar to the Constrain Hydropower policy case with Dry climate explained in the previous section. As the risk level increases the model first replaces natural gas with hydropower ROR, in an attempt to move away from risky natural gas resources with volatile prices. But as risk level continues to increase further, the model suggests cutting back slightly on hydropower ROR and replaces it with larger shares of wind, geothermal and solar PV (~4 GW for the risk averse scenario), and a slight increase in hydro DAM. Given the reduced availability of runoff, the model prefers installing ROR than the more expensive DAM that would not have any water available to benefit from its storage capabilities.

Figure 4.33: Installed capacity by risk level and climate change scenario in Ecuador for 2017–2050

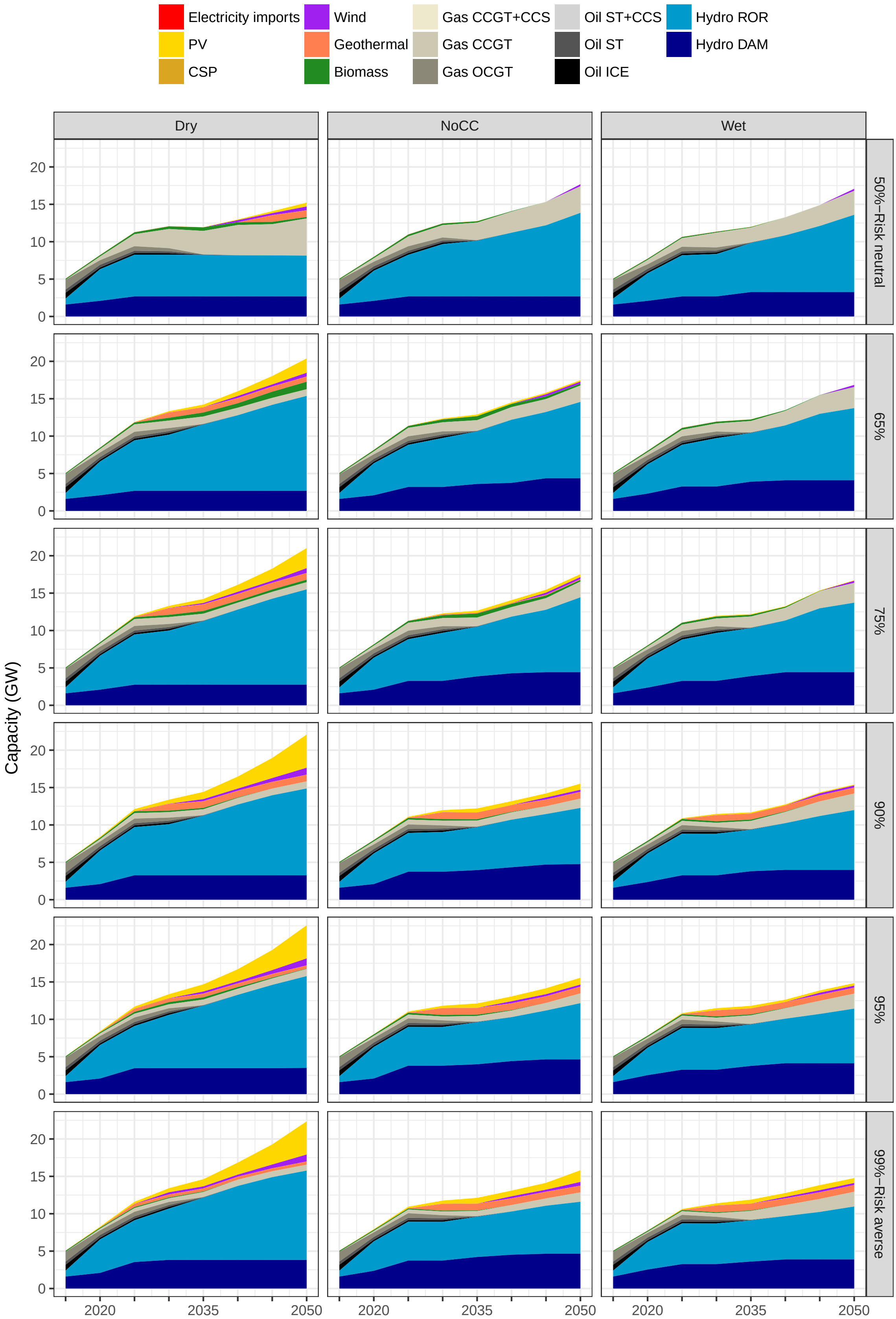
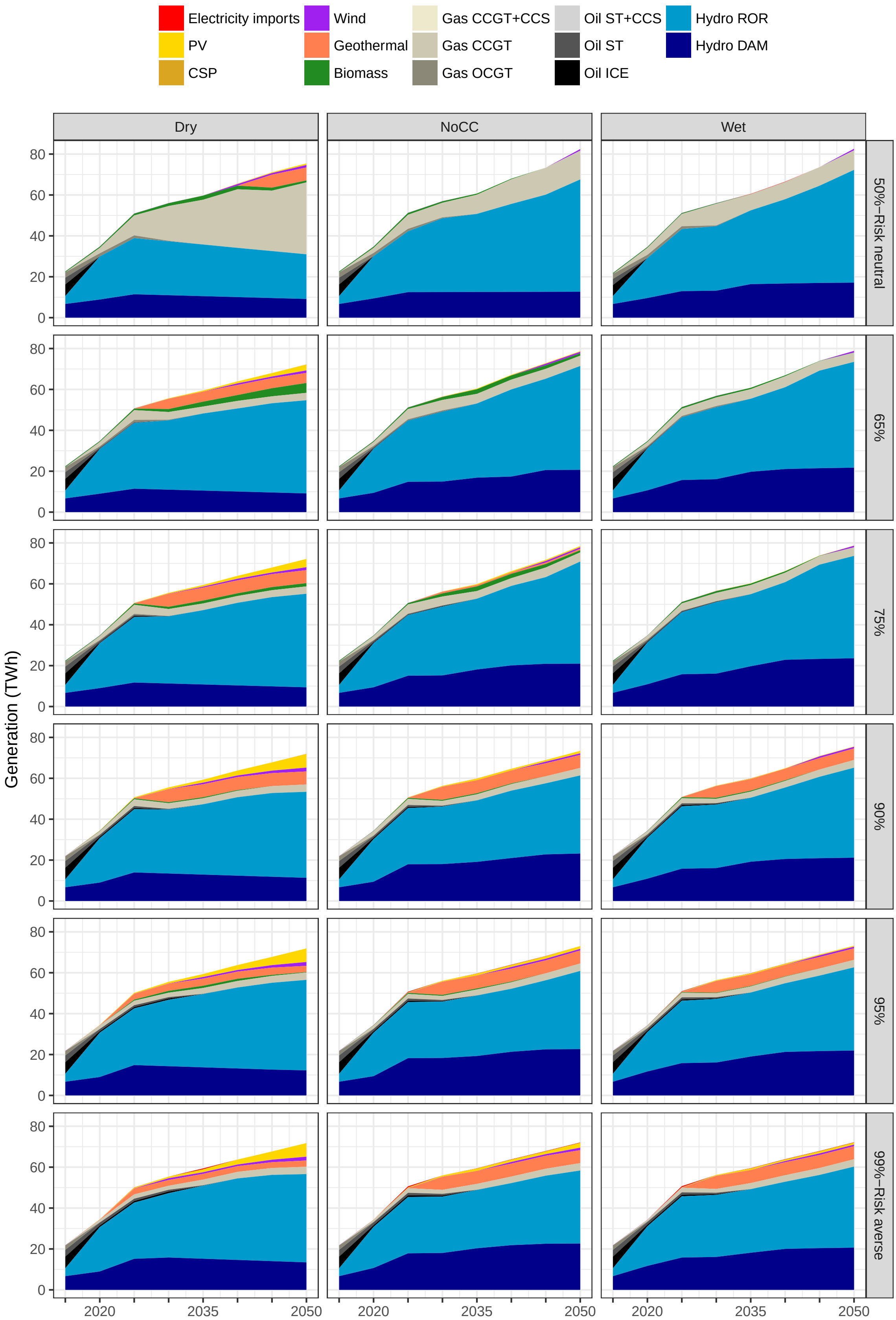


Figure 4.34: Electricity generation by risk level and climate change scenario in Ecuador for 2017–2050



In terms of total electricity generation (Figure 4.31 on page 227, bottom), TIMES-EC shows that by 2050, hydropower ROR will maintain an important share in power generation (with exception of the risk neutral Dry climate scenario in which the model picks large shares of natural gas). The share of non-hydro renewables introduced into the generation matrix to reduce risk depends on the climate scenario. Non-hydro renewables reach a maximum of 25% of generation share in the Dry climate scenario, while only a 10% share in the Wet climate scenario. Geothermal and biomass generation are the most important non-hydro renewable generation sources in the Mean and Wet scenarios, while significant shares of PV and wind only appear in the Dry scenario case.

Table 4.9 on the following page summarises the findings for hydropower for year 2050, showing the variation of installed capacity and generation for all risk levels and climate change scenarios. More water availability translates into less capacity of hydropower being installed, but more electricity being produced. The differences between the NoCC, Wet scenarios and Dry scenarios can be captured in these results. The NoCC and Wet scenarios seek to reduce installed capacity and hydropower generation as risk level increases, which would seem logical as the model tries to move away from the uncertain capital cost of hydropower. However, in the Dry scenario, as risk level increases, installed capacity and electricity production from hydropower increase, because in a scenario with lower water availability the other only reliable alternative for abundant generation is gas-fired generation, which by the assumptions of this research would have a worse cost risk profile in the long-term. Therefore the model prefers the risk of hydropower than the risk of a power matrix dominate by gas.

In this subsection, electricity portfolio configurations for a snapshot in 2050 have been assessed. For electricity installed capacity, generation and demand pathways for the entire modelling horizon 2017–2050 please see Figure 4.33 on page 229, Figure 4.34 and Figure 4.41, respectively.

4.3.3 *Efficient frontier – cost v. risk*

Figure 4.35 on page 233 illustrates the modelling outcomes when running the TIMES-EC model for increasing levels of risk level aversion (confidence interval) and three scenarios of climate change (Dry, NoCC and Wet). Each marker represents a single optimal generation portfolio in 2050 in terms of expected average generation cost (vertical axis) and cost risk (UpAbsDev of cost, horizontal axis), which lie on their respective "efficient frontier" according to each climate change scenario. This means that any portfolio that is not on the efficient frontier is necessarily suboptimal (by the measures calculated in

Table 4.9: Main results from the TIMES-EC model with Portfolio Theory extension for hydropower installed capacity and annual average generation in 2050

	Risk level	2017		Climate scenario in 2050			
			NoCC	Dry	Δ	Wet	Δ
(GW)	50% – Risk neutral	5.1	13.8	8.1	-41%	13.6	-1%
	65%	-	14.5	15.3	6%	13.7	-6%
	75%	-	14.4	15.5	8%	13.7	-5%
	90%	-	12.2	14.8	21%	12.0	-2%
	95%	-	12.1	15.7	30%	11.4	-6%
	99% – Risk averse	-	11.6	15.7	35%	10.8	-7%
(TWh)	50% – Risk neutral	24.5	67.6	31.0	-54%	72.3	7%
	65%	-	71.4	54.7	-23%	73.5	3%
	75%	-	70.9	55.1	-22%	73.6	4%
	90%	-	61.4	53.4	-13%	65.1	6%
	95%	-	60.7	56.5	-7%	62.6	3%
	99% – Risk averse	-	58.3	56.6	-3%	60.2	3%

Note: Δ is the difference in percent respect to the NoCC climate change scenario.

this study). This type of curves are the typical results from studies that use Portfolio Theory to assess the trade-offs between cost and cost risk in the power sector (Awerbuch and Yang, 2007; Vithayasrichareon et al., 2015; Jansen et al., 2006). The idea they want to transmit is that to reduce cost risk in a system, it is necessary to increase its cost. A colour gradient has been used to represent increasing six levels of risk considered in this study – from risk neutral (red) to risk averse (blue).

Analogously, Figure 4.36 on the next page shows the efficient frontier in terms of the trade-off between average generation cost (vertical axis) and the considered level of risk (or confidence interval of the probability distributions, horizontal axis).[6] This figure shows that when a broader measure of risk is taken into the account in the model, the cost of the least-cost portfolio increases. In this case, the colour gradient represents the cost risk that is reduced as a higher level of risk is considered in the model. The generation portfolios with the lowest expected average generation cost occur for a Wet climate change scenario, and the highest expected costs are for a Dry scenario (see Figure 4.35). Therefore, an interesting finding of our work is that the efficient frontier depends strongly on the climate change scenario that is taken into account for Ecuador. Although in the risk-neutral case (see Figure 4.36), all scenarios have similar expected average generation cost regardless of climate change (~4 US¢/kWh), as risk level consideration is

6 Probability distributions for fossil fuel price and electricity generation costs were shown previously in Section 4.3.1 on page 221

Figure 4.35: Efficient frontier showing the trade-off between expected average generation cost and cost risk

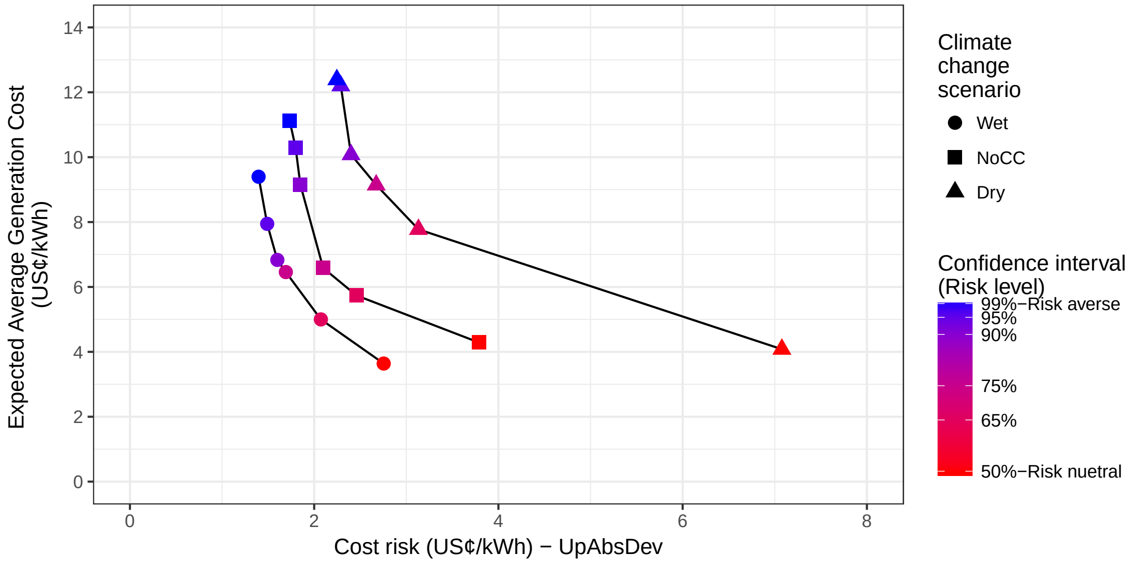
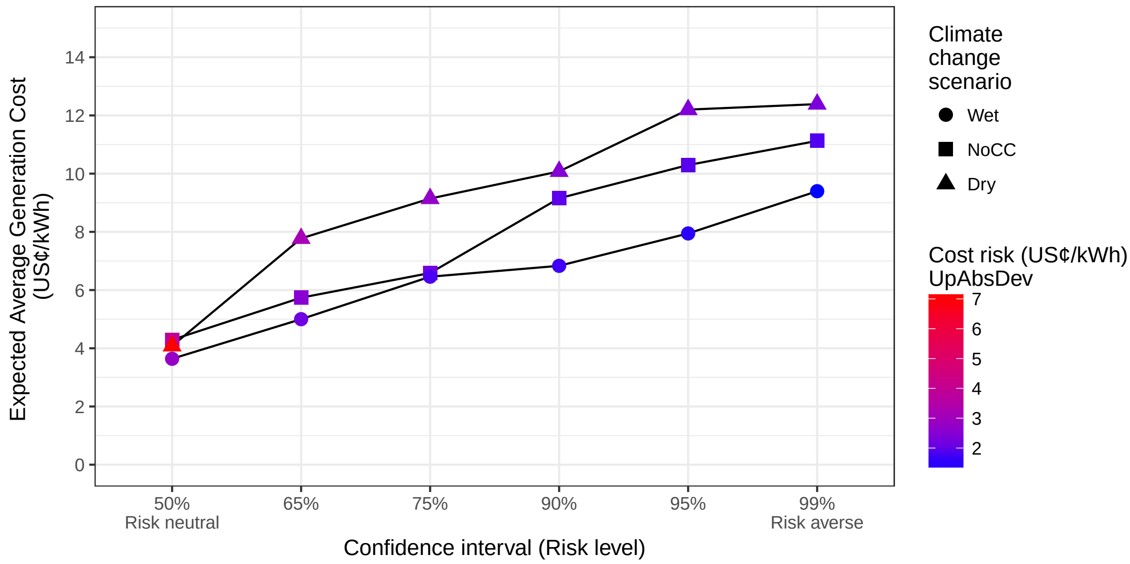


Figure 4.36: Efficient frontier showing the trade-off between expected average generation cost and risk interval (confidence interval)



increased the climate change scenario defines how high the expected average generation cost will have rise to reduce cost risk.

Focusing on the efficient frontier shown in Figure 4.35, the reduction of cost risk is first achieved with a relatively small increase in expected additional cost. However, further reducing cost risk comes at increasing cost. The efficient frontiers within each climate change scenarios are steep, suggesting that beyond a certain point, varying the proportion of generation technologies has minimal impact on the cost risk of a portfolio. Given uncertainties around hydropower investment cost, operating large shares of hydropower carries a similar level of cost risk. In general, expected average generation cost roughly doubles/triples when moving from the risk-neutral to risk-averse level. Expected average generation cost increases in the Wet climate scenario from 4 to 8.5 US¢/kWh, in the NoCC from 4 to 11 US¢/kWh and in the Dry scenario it increases from 4 to 12.5 US¢/kWh.

The clear implication is that it is not possible to reduce portfolio cost risk without having a negative impact on generation cost, thus the cost-risk trade-off is represented. Based on this technique, the suggestion is that risk averse policy makers that take into consideration the full range of uncertainty into the model (99% confidence interval) should expect their budgets to increase by around 100% but benefit from a small cost deviation of US¢ 1 – 2.5/kWh. If the decision-makers are more risk tolerant and decide to leave risk out of the model (50% confidence level), they could stay with their initial expected least-cost budget of around 4 US¢/kWh; however, they should expect significant deviation, up to additional 2.5 US¢/kWh for the Wet scenario, 4 US¢/kWh for the NoCC scenario and even up to 7 US¢/kWh deviation for the case of a Dry climate change scenario.

As shown in the previous subsection, the share of intermittent renewable energy (namely, solar PV and wind) increases in the generation portfolio to hedge against risk. Therefore, there will be an increasing need to curtail them and also to provide enough reserve capacity back-up, causing the marginal risk that can be reduced per installed unit of capacity of wind turbines or PV panels to drop, making it costlier to reduce risk. This in part explains the convex and steep shape of the efficient frontiers presented in this study (Figure 4.35 on the previous page), owing to an ever-diminishing risk reduction potential of non-hydro renewables.

The least-cost decisions that the model is making to reduce risk has to be translated into a change in the investment and operational decisions for the technologies in the power sector. The breakdown of the different cost components – investment, fixed costs, variable costs and fuel costs, that change as TIMES-EC seeks to reduce cost risk is presented in Figure 4.37. In general the model invests in a more expensive system configuration to move away from a riskier one (as was seen in the previous section in Figure 4.31 on page 227). This basically shows the model choosing to increase its investment cost as to reduce its fuel spending.

For example, in the Dry climate change scenario, the model invests in larger shares of hydro ROR, expensive PV and expensive wind capacity, which mean an incremental annual investment and fixed cost of the power system that reaches US$ 220 million per year when compared to the risk neutral scenario. This investment in renewable energy causes fuel and variable costs to reduce proportionally, although these cost savings do not fully compensate the higher investment and fixed costs, and therefore the net total

Figure 4.37: Breakdown of the additional cost of the six portfolio runs under scenarios of climate change

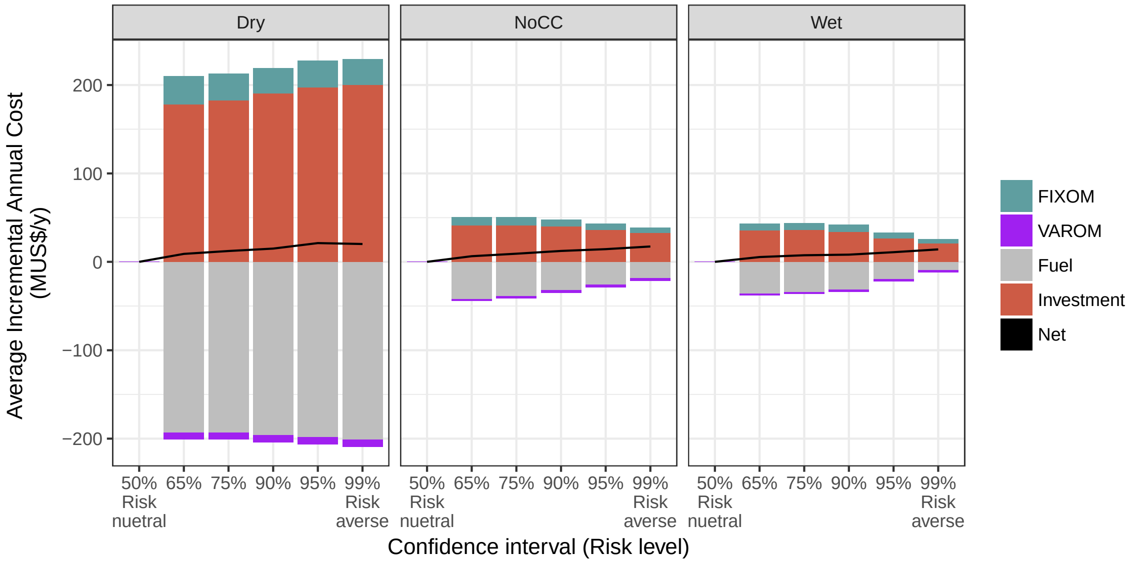


Table 4.10: Average incremental annual cost per risk level and climate scenario

		Average incremental annual cost (US$ million/yr)					
Confidence interval		50%	65%	75%	90%	95%	99%
Risk level		Risk neutral		→			Risk averse
Climate scenario	Dry	0	9	12	14	21	21
	NoCC	0	6	9	12	14	17
	Wet	0	5	7	8	11	14

annual cost of the power system increases by US$ 21 million (see black line in Figure 4.37). Table 4.10 summarises the net average annual incremental cost of the power system per risk level and climate scenario. In comparison, for the NoCC and Wet scenarios, the model makes lower investments to move away from a riskier portfolio, fuel savings are consequently smaller, but net annual increases are still positive. There is an additional finding discovered here, which is that a Dry climate scenario is not only more expensive in terms of cost risk (as seen in Figure 4.35 and Figure 4.36), but will demand more capital intensive investments to hedge against risk, as when compared to the NoCC and Wet climate scenarios. The availability of hydropower power is key to determine the amount of investments required to minimise power system cost risk.

4.3.4 *Robust electricity generation portfolios*

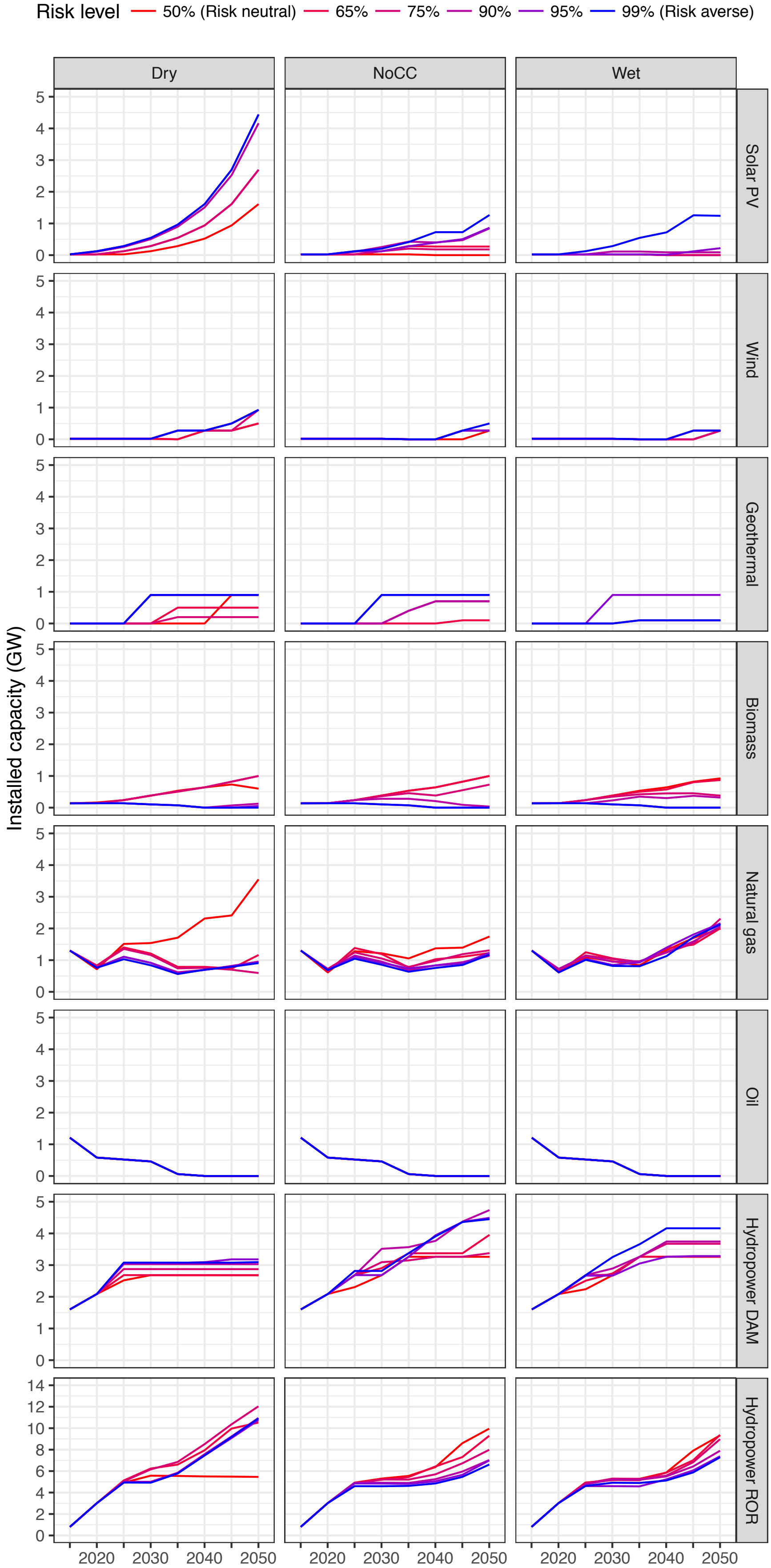
The approach used in this thesis internalises risk into the optimisation process of TIMES and therefore it is possible to identify system configurations and technologies that are robust to the uncertainties and the input assumptions. Robust technologies are understood as 'no-regret options' for decision makers, i.e. investment in these technologies is a prudent decision regardless of how the uncertainties play out (Labriet et al., 2015). In this thesis, this means electricity generation technologies that TIMES-EC decides to deploy, regardless of the recurring uncertainties of fossil fuel prices and electricity technology investment costs, and the long-term uncertainty of climate change.

Figure 4.38 on the facing page shows the evolution of installed capacity of individual electricity generation technologies to assess robustness of investment decisions in the mid-term or long-term. If the deployment or retirement of a technology is consistent for all the assessed scenarios, it is considered to be robust (overlapping trajectories). Otherwise, different paths to expand capacity indicate a technology that is susceptible to uncertainty and the risk seeking preferences of the decision maker. A risk averse decision maker would follow the capacity expansion plan for the Dry scenario and the risk aversion level (represented with blue lines in Figure 4.38). A risk neutral (or risk seeker) decision maker would opt for expansion plans for the Mean and Wet scenario and a risk neutral level (represented in red lines in Figure 4.38).

Notice that TIMES-EC deploys the same value of hydropower ROR capacity up to 2025 regardless of the risk level or climate scenario (see last row in Figure 4.38), after which further deployment depends on the desired risk level of the decision maker and varies significantly, ranging between 6 – 12 GW by 2050. Lower capacity levels of ROR hydropower are preferable if decision makers are risk averse (blue colour gradients for lower capacity levels). In contrast to ROR hydropower, solar PV and DAM hydropower shows that increased capacity levels are preferable for risk aversion (blue gradients for higher capacity levels). All scenarios show that the reduction of oil-fired capacity in the generation matrix is a robust decision (consistent pathway regardless of scenario). This is somewhat similar to the installed capacity of gas-fired plants, which show a fairly constant level of capacity expansion throughout all risk level scenarios.

Geothermal is not deployed in any scenario before 2025, after which their deployment depends on the risk level and climate scenario and is suggested to be deployed to its maximal potential in all climate scenarios by 2050. Hydropower DAM also shows a robust capacity deployment up to 2020, after which the model suggests larger capacities for risk reduction between 2.5 and 4.5 GW in 2050. Figure 4.38 also informs about the

Figure 4.38: Evolution of the least-cost installed electricity capacity for individual electricity generation technologies according to risk level and per climate change scenario



positive, negative or inexistent correlations for technology deployment. For instance, higher shares of PV, geothermal and hydropower DAM call for lower shares of hydropower ROR, natural gas and biomass, while wind and oil follow a fairly consistent path regardless of risk level. It is also seen that hydropower DAM shows a more robust pathway development compared to hydropower ROR, of course this depends of the feasibility of continuing large-scale hydropower projects in the Amazon, where most of the country's potential lies (see Section 3.2.5 on page 124) – restrictions on large hydropower deployment was not considered in the Portfolio Theory approach.

As can be seen in Figure 4.38, increased investment in non-hydro renewables (except biomass technologies) provides an effective hedge against risks (in general blue gradients are seen for higher capacities and red gradients for lower capacities, particularly for solar PV and geothermal energy). Investment in non-hydro renewables could therefore be considered a kind of "insurance" against potentially extreme future fossil fuel prices, capital costs and detrimental (Dry) climate change scenarios. The additional cost of investing now in non-hydro renewable technologies effectively insures industry stakeholders against an uncertain future. In contrast, continuing to operate with large ROR hydropower and an emissions intensive oil- and gas-fired generation portfolio, is likely to significantly increase industry costs and cost risk. Notice that bioenergy has an opposite trend as compared to other non-hydro renewables due to the thermal plants having higher cost escalations than wind and solar, as was shown in Figure 4.29 on page 225. Although bioenergy itself has been considered cost-risk free in this analysis, the capital cost overruns of bioenergy technology are sufficient for the model to move away from this source. This would also be equivalent for gas-fired thermal plants, although gas in this study is priced lower that biomass, and therefore the model shows a preference for gas-fired than for biomass-fired thermal technologies. Considering lower prices for biomass, could produce the model to show a larger preference on biomass to reduce risk. However, biomass resources was excluded from the uncertainty analysis due to the lack of historic data to assess the volatility of its price.

Figure 4.38 also shows that only when TIMES-EC does not take cost risk into consideration (red colour gradients) that it suggests for the continued deployment of large ROR hydropower and gas-fired thermal capacity. However, fossil fuel prices and technology costs depend on events at a global scale. For example, if international communities work on climate change and if all governments work together to the meet the Paris Agreement commitments, long-term (2050) demand for oil and natural gas will decline, leading to lower prices and a changing correlation among oil and gas prices. Moving away from fossil fuels will cause heavy investments in cleaner technologies which will, in turn, lead to further reductions in the investment cost of hydro and non-hydro renewables, as has been already experienced in the last few years (BNEF, 2016). This is why this research has considered a broad uncertainty for fossil fuel prices and electricity generation technologies. The effects of the uncertainty has been captured by the model by suggesting different development paths for each generation technology.

4.3.5 *Electricity and final energy demand*

The advantage of using an integrated energy system optimisation model is that the interaction of both electricity supply and demand can be captured. Figure 4.39 on page 242 shows projected electricity demand growth for the modelling horizon at the scenario level. In general demand appears to reduce for drier climate occurrences and also due to higher levels of risk level. This means that electricity demand is responding to price changes in electricity supply due to risk reducing decisions, which make the price of electricity more expensive and therefore cause a reduction in electricity consumption. In addition it reacts to higher prices due to lower water availability that reduces the amount of cheap hydropower in the mix. Demand is shown to evolve differently and diverges towards 2050 with a range between 65 – 75 TWh, with drier scenarios demanding less electricity ~65 TWh and NoCC and Wet scenarios having a greater and broader range 68 – 75 TWh.

Figure 4.40 on page 242 shows a snapshot in 2050 of total electricity demand by the sectors detailed in TIMES-EC. By 2050, the largest consumer is industry (traditional + strategic), followed by the residential, commercial, transport and other sectors. Notice that in the Dry - risk neutral scenario, power demand is lower (68 TWh) than the corresponding NoCC and Wet risk neutral scenarios (75 TWh), showing that demand is reacting to high electricity prices in the occurrence of a Dry climate scenario with lower hydropower generation. In this case the industrial sector cuts back electricity consumption and switch to LNG in thermal processes. Nonetheless, most of the changes detected in the demand side are due to the consideration of a greater level of risk in the model. The NoCC and Wet scenario show the industrial and residential sectors reducing demand as risk level increases. In other words, TIMES-EC suggest that a shift to electricity in the industrial and residential sectors is appropriate from a least-cost perspective if there is cheap hydropower generation available (availability of runoff) and there are low to no cost overruns expected for hydropower infrastructure.

The shift away from electricity for higher risk levels causes the broader energy system to switch to gas and petroleum products, which would be counter productive. Given that fossil fuel equipment is less efficient than electric ones, final energy demand increases for higher risk levels. This is evidenced in Figure 4.42 on page 244 where total final energy demand by sector and fuel in Ecuador by 2050 can be seen. It is seen that the industrial and residential sector have increasing final energy demand, since they are the ones moving away from electricity. The residential sector switches from electricity to LPG, while the industrial sector switches from gas to oil products.

This effect can also be observed in terms of fuel use in Figure 4.42 on page 244 (bottom), where the reduction of electricity (blue bar) reduces and there is an uptake in oil products. Crude oil and petroleum products are cheaper than gas, therefore given that gas and oil prices are positively correlated (similar risk level), the system prefers to consume oil rather than gas in the energy system. Risk levels have been the focus of this research and it has dedicated to include the risk of electricity generation technologies, therefore most changes in system configuration are within the power sector.

It is highlighted that including risk into other energy sectors and demand-side conversion technologies could produce different changes in the final energy mix, which is suggested as an area for further research. Only two specific uncertainties have been added in this analysis: climate change and cost overruns. But many more have not (e.g. investment cost trends, bioenergy prices, fossil fuel resource uncertainty, consumer behaviour, etc.). Also, more generally, the portfolio approach has the shortcoming that it needs to focus on costs. This means, for example, that climate still needs to be represented through scenarios, as opposed to including it directly in the decision making of the model. Therefore, the same limitation applies to any other elements that would be reflected in the objective function through constraints, instead of costs (e.g. resource potentials, demand projections, availability factors, construction delays). This all means that where in reality there could be even great uncertainties, the model sees good, risk-free hedging opportunities (or leave critical choices for the decision maker – what climate scenario to follow).

The results of this section should be considered within the scope of the analysis defined as the motivation of this work - i.e. to assess the least-cost expansion of a hydropower-based power system. It serves as an alternative set of scenarios to other power expansion exercises that would only consider a least-cost approach, without taking into consideration the probability of cost overruns of technologies and fossil fuel prices. However, the underlying assumption is that both capital cost and climate change are the most important uncertainties when looking into the deployment of large hydropower infrastructure and rule out the fact, for example, that unforeseen construction time delays of hydropower infrastructure could have an impact on the way that the power system evolves. In a sense, this is why the "No Large Hydropower" scenario was assessed in the previous set of scenarios, in which a cap on hydropower deployment was set to see how the system reacts. However, there is a limitation also to include probability of construction delays in the portfolio theory approach, because lead time is not a cost component of the objective function, although one could argue that cost overruns somehow factor-in the cost overruns of delayed projects.

Figure 4.39: Projected total electricity demand in Ecuador per climate scenario and risk level

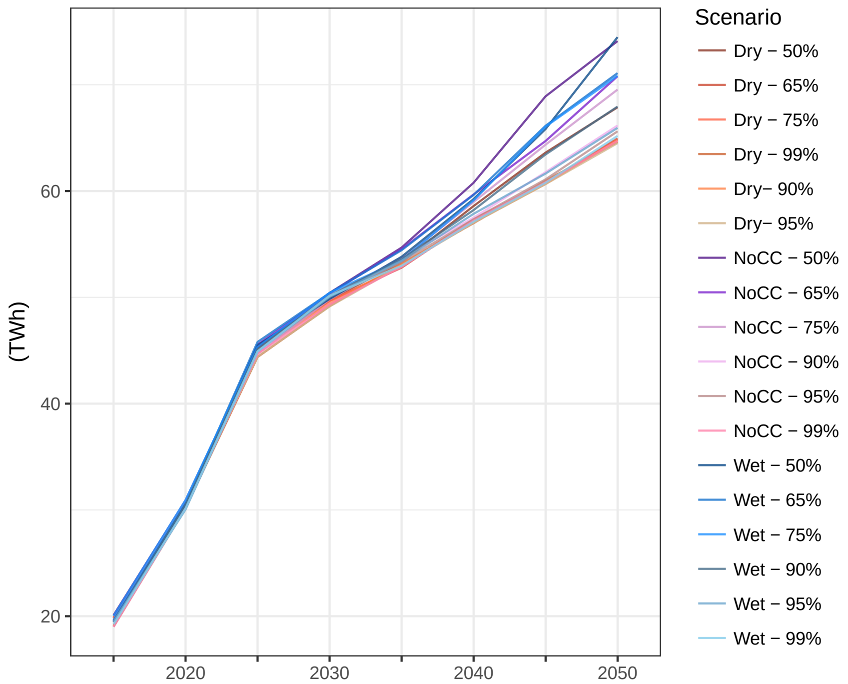


Figure 4.40: Total electricity demand by demand sector per risk aversion level and climate change scenario in 2017 and 2050

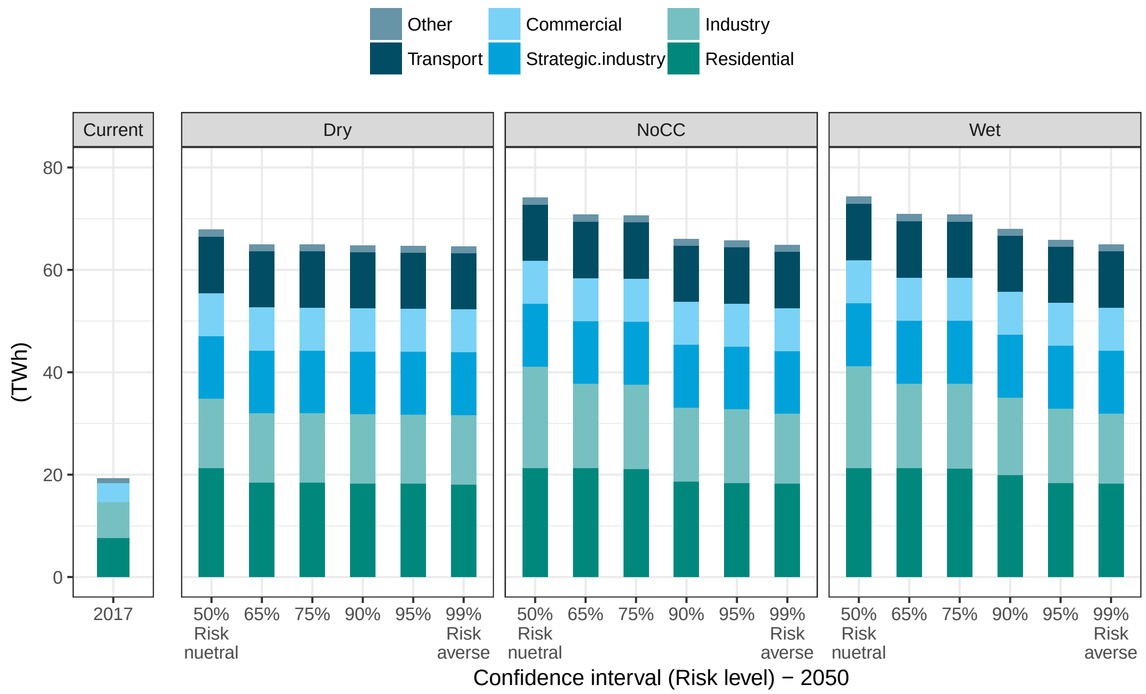


Figure 4.41: Electricity demand per economic sector in Ecuador for 2017–2050

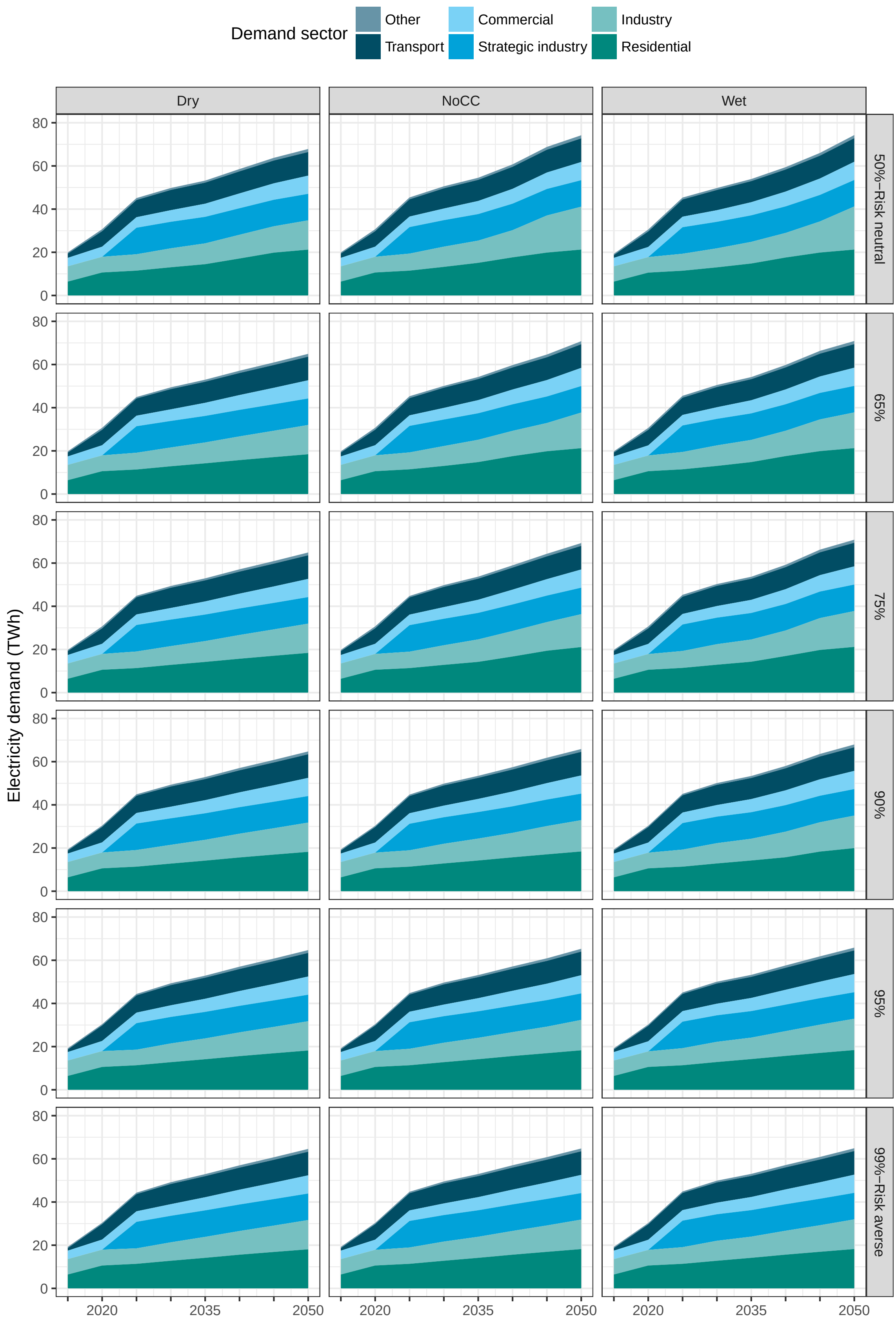
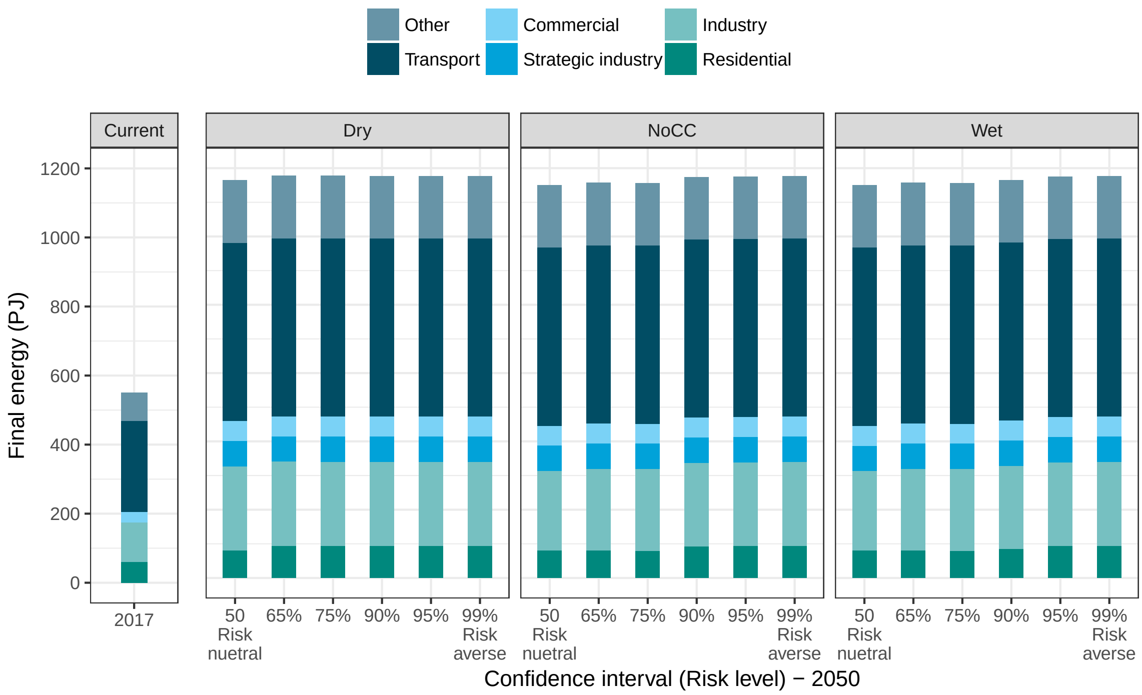
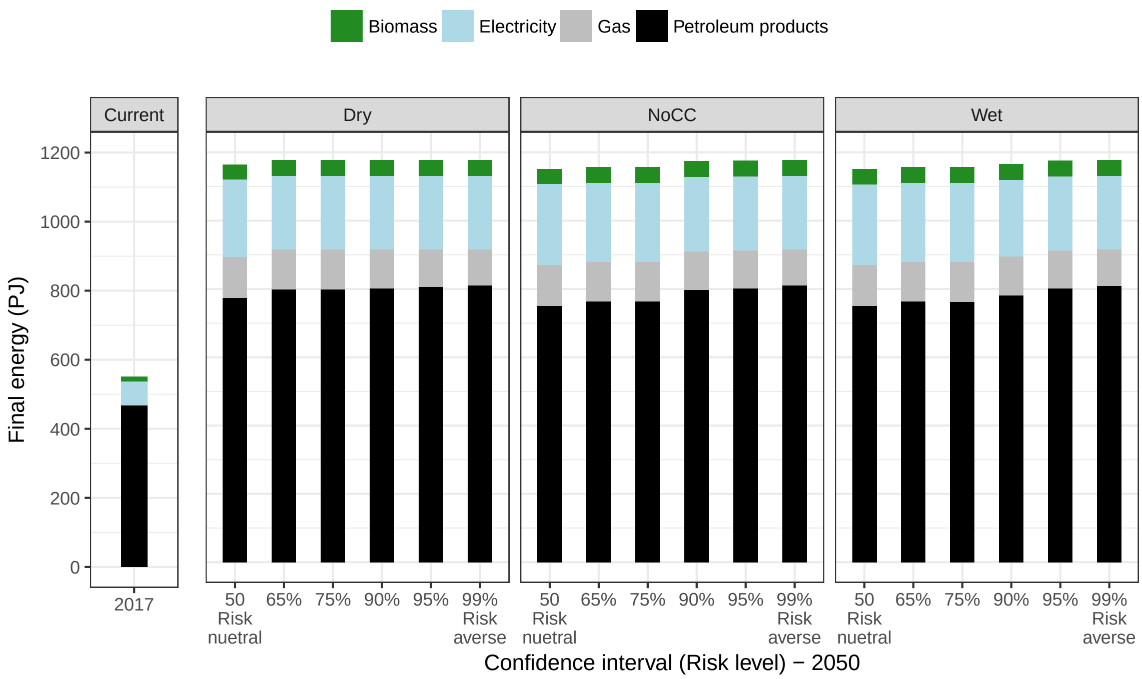


Figure 4.42: Final energy demand by sector and fuel in Ecuador by climate change and risk level in 2017 and 2050

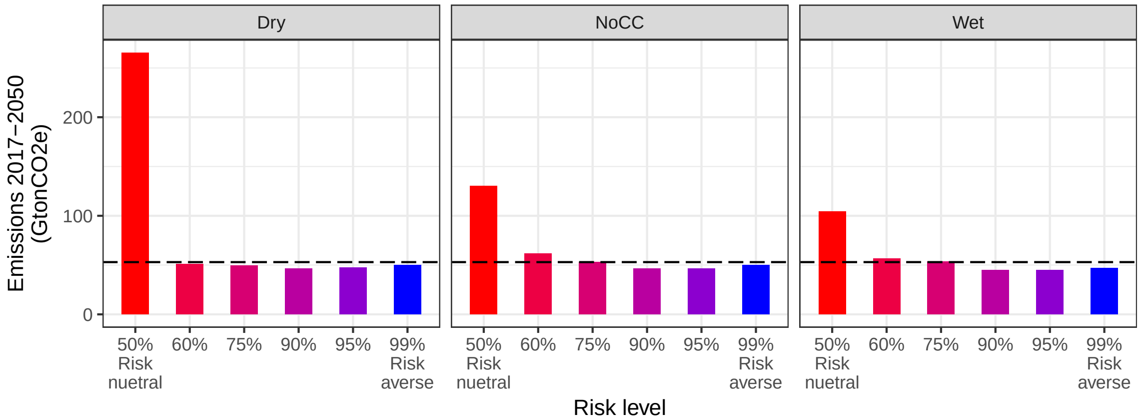




4.3.6 *Electricity related GHG emissions*

Figure 4.43 shows cumulative electricity-related GHG emissions for the period 2017–2050 for all modelled scenarios. The emission level of most scenarios is lower than the NDC level (53 GtonCO_2e), except for the risk-neutral cases in which the lack of consideration of fossil fuel price risk causes the model to choose gas as the least-cost generation option. In the Dry - risk neutral scenario, emission levels almost quintuply (250 GtonCO_2e) when compared to the NDC level (see Figure 4.31 on page 227 which detailed power generation for all scenarios). It is noted that, at first, increasing risk levels reduces emissions abruptly as the power system moves away from gas-fired generation. However, as risk level increases further, emissions increase slightly due to the need to uptake gas-fired thermoelectric plants to back-up intermittent non-hydro. Hedging risk in the model mainly translates in replacing hydropower with other non-hydro renewable technologies, therefore beyond the initial reduction of emissions, increasing the risk level further does not to reduce emissions greatly.

Figure 4.43: Electricity related GHG emissions for the period 2017 – 2050 per risk level and climate change scenario.



4.3.7 *Summary*

The results presented in this subsection have demonstrated that different perceptions on risk can lead to different least-cost electricity generation portfolio choices. It has been conclusively demonstrated that, for the Ecuadorian power system, hedging against fossil fuel and power technologies cost risk means moving from a power system with gas-fired thermal generation and ROR hydropower, towards one which is more diversified and balanced with more DAM hydro, geothermal, wind and solar PV (see Figure 4.31 on page 227). However, reducing exposure to cost risk implies increasing system cost, which is the main argument of financial Portfolio Theory approaches that seek to capture the trade-off between cost and cost risk by defining an efficient frontier. This efficient frontier was assessed and presented in Figure 4.35 on page 233, showing the increase in average generation cost of the power system required for cost risk reduction and the impact that impact that different climate change scenarios has in the trade-off.

Selected key outcomes of this subsection are summarised below (while all key findings are restated in the conclusion of this thesis in Chapter 6 on page 271):

- For all assessed scenarios (six levels of risk for three climate change scenarios), hydropower maintains an important capacity share (>50%) by 2050. ROR hydropower installed capacity ranges broadly (between 5 GW and 12 GW by 2050) with lower shares considered to be favourable for a risk averse portfolio, however the model suggests that higher shares of DAM hydro should be taken into consideration for risk reduction, although in smaller range (between 2.5 and 5 GW). This can be seen in Figure 4.31 on page 227 and Figure 4.32 on page 228. Gas-fired thermal electricity is consistently reduced to hedge against gas price volatility, while non-hydro renewables considered are deployed to hedge agains hydro ROR cost overrun uncertainty, in particular solar PV (4 GW), wind (1 GW) and geothermal capacity (0.9 GW) in the occurrence of a Dry climate change scenario.

- It is not possible to reduce portfolio cost risk without having a negative impact on generation cost, thus the cost-risk trade-off has been captured with the integration of a Portfolio Theory approach in TIMES-EC. At first, the reduction of risk is achieved with a relatively small increase in expected additional cost. However, further reducing risk comes at increasing cost. In general, expected average generation cost roughly doubles when moving from the risk-neutral to risk-averse level (see Figure 4.35 on page 233). Risk hedging decisions translate into investment and operation decisions. A Dry climate scenario will require of more capital intensive investments (more PV and wind) to hedge against fuel cost risk, as the cost breakdown of cost hedging decisions evidenced in Figure 4.37 on page 235.

- Electricity demand responds to risk-level and climate change scenario. Electricity demand is lower for dry climate scenarios and for high risk levels, thus showing its response to increase in electricity price due to high cost risk-hedging strategies and lower water availability that restricts cheap hydropower generation. Figure 4.40 shows electricity demand by sector, where demand changes are specifically experienced by the industrial and residential sectors. Moving away from electricity translates into an uptake of less efficient fossil fuels, and therefore an increase in final energy demand, mainly due to the switch from electricity to gas and oil products. This switch is shown in Figure 4.42 on page 244 where final energy demand by sectors and fuels was shown.

- Emission levels for risk hedging scenarios are lower than the implied NDC level (53 GtonCO_2e) in all scenarios, except in risk-neutral levels in which higher shares of gas-fired thermal electricity is allowed. Figure 4.43 on page 245 showed how emission levels change with the inclusion of cost risk in the model. A risk neutral - Dry climate could raise emission levels up to five-fold (250 GtonCO_2e). Therefore showing that if risk is not considered and a dry occurrence comes to happen, the system could lock-in to gas-fired generation.

Finally, according to the findings of this subsection, a risk-hedging strategy for the power sector would try to follow the installed capacity suggestions for the risk averse case (99% confidence interval). Table 4.11 on the following page shows the list of generations technologies, their suggested installed capacity ranges by 2050 and the trend they should follow for risk hedging against climate change uncertainty, fossil fuel price volatility and capital cost overruns. This was elaborated based on the results of Figure 4.32 on page 228 and Figure 4.38 on page 237 that showed the installed capacity trajectories for generation technologies. The ranges of capacity should be taken as suggestions for the configuration of generation portfolios that are least-cost, however the trend direction should gives and idea of the preferred value for a more robust portfolio.

The broader considerations of assumptions, modelling technics and other relevant issues of the findings will be discussed in the next chapter.

Table 4.11: Risk-hedging electricity generation portfolio for Ecuador in 2050

Technology	Capacity range	Trend for risk-hedging	Comment
Hydro DAM	2.5–5 GW	⇑	Hydro DAM allows the system to move away from risky hydro ROR and reduce the need for risky gas-fired backup.
Hydro ROR	5–12 GW	⇓	Hydro ROR varies greatly with risk level and climate occurrence. Lower shares are preferred for risk hedging when they can be replaced by solar PV.
Oil	0 GW	⇓	Oil-fired generation phase out is suggested in all assessed scenarios.
Gas	1–5 GW	⇓	Gas-fired generation is preferred at low levels (~1 GW), except in the case of risk neutrality and a Dry climate.
Biomass	~0.2 GW	⇓	Only good for small levels of risk-hedging in any climate scenario.
Geothermal	0.9 GW	⇑	Install at full resource limit if possible in the Dry and NoCC climate scenarios.
Wind	0.5–1 GW	⇑	Higher capacities in the Dry climate scenario.
Solar PV	1–4.5 GW	⇑	PV highest hedging potential is in the Dry climate scenario when combined with larger shares of Hydro DAM for back-up.

5

DISCUSSION, LIMITATIONS AND FUTURE WORK

5.1 DISCUSSION OVERVIEW

The previous chapter presented the results from the three research questions of this PhD thesis, which are restated below:

1. How broad is the uncertainty of hydro-climatic variables portrayed in a large ensemble of climate projections and the impact on the availability of runoff for hydropower generation?

2. How does hydropower output variations due to climate change impact the long-term least-cost power system development pathway?

3. How does incorporating recurring uncertainties such as the volatility of fossil fuel prices and the capital cost of electricity infrastructure impact the investment portfolio for the power sector?

Based on these research questions, the analyses undertaken in the previous chapter has delivered insights on the magnitude of impacts of climate change associated to precipitation, runoff and hydropower generation availability. Including also an analysis on how this issue evolves under different policy cases and when other recurring uncertainties are considered in an energy system model.

It was specifically shown that even under a dry climate change scenario, hydropower will maintain its role as an important source of electricity generation in Ecuador. However, in the long-term, a generation matrix with larger shares of non-hydro renewables can help reduce capital investment and reduce risk of cost overruns of the generation portfolio. The study also showed that the deployment of gas-fired thermal generation is needed for back-up and that alternatives such as biomass and geothermal energy can be considered, which are less risky options with lower variable costs than gas-fired options. This contrast between a gas-dominated power matrix and the more diversified matrix with larger shares of non-hydropower alternatives has resulted in contested views regarding the evolution of capacity expansion for the long-term in Ecuador.

As with other modelling exercises, these findings need to be considered within the context of assumptions, and the modelling approach itself has some limitations. Because different assumptions present serious implications for determining the least-cost system configuration, a number of influencing factors are further investigated in this chapter and used as a way to frame the discussion around limitations and future work. This chapter discusses the following issues related to each one of the research questions:

1. Hydrological and hydropower modelling under long-term climate change projections,
2. Modelling of the power sector in energy system optimisation models,
3. Portfolio theory to assess recurring uncertainties in energy system optimisation models.

A number of limitations on generalisation of this work are also provided at the end of this chapter.

5.2 HYDROPOWER MODELLING UNDER UNCERTAIN CLIMATE CHANGE

5.2.1 *Climate change scenario definitions*

This study has used a large ensemble of 40 GCMs to characterise the uncertainty space of climate change and used the mean and standard deviation of the ensemble as a proxy for the definition of hydrological scenarios. This decision will have down-stream implications for all subsequent modelling steps, i.e. hydropower simulation and energy system optimisation. All the results obtained with the chain of models used in this thesis, have the assumptions of climate change scenarios as their underlying premise.

While the mean and standard deviation has been used as a statistical measure of GCM ensemble uncertainty. It should be mentioned that there is no statistical fix in ensemble results and one should not confuse the range of diverse outcomes across an ensemble of model simulations (projections) – such as the one used in this study from the CMIP5 – with a statistical measure of uncertainty in the behaviour of the Earth. As Smith and Petersen (2014) state – *This does not remotely suggest that there is no information in the ensemble or that GCM models are worthless, but it does imply that each dimension of reliability needs to be assessed.*

In the case that ensemble results are to be considered as a measure of probability, the necessary condition would be that the integral of $P(x|I)$ is equal to 1. Thus, meaning that the reality of the Earth's state is actually captured by one of the ensemble scenarios. The distribution of a climate ensemble is not a true probability distribution but instead an expert judgement with respect to potential future climatic conditions (Moss et al., 2010) and therefore assigning probability statistics to them might be misleading (Taylor et al., 2012; Collins et al., 2013). Nonetheless, for the purpose of analysing impacts of climate change, GCMs are still the only credible tools currently available to simulate the physical processes that determine global climate (Parkinson and Djilali, 2015). The recent abundance of GCMs and growing number of future concentration scenarios calls for new methods and approaches that shed light on new methods and approaches to use this information on studies that assess climate change impacts on natural and human systems, especially when there is a need to parameterise the probability space.

5.2.2 *From hydrological modelling to hydropower simulation and to availability factors*

5.2.2.1 *Hydrological modelling*

The simulation of key hydrological indicators, such as river runoff, driven by various climate projections from GCMs brings a number of limitations associated with making such projections (Kundzewicz et al., 2018). With regards to the projections of runoff, there are two sources of uncertainty that result in the failing to capture the behaviour of the river with high degree of precision: the hydrological model and the data used for its development. Different hydrological models can be applied to study the impacts of climate change on hydroelectric generation. Physical hydrological models are data intensive, so they are limited to small and well 'measured' catchment area projects (Harrison and Whittington, 2002). As a whole hydropower system was investigated in this thesis, which is spread out in larger and different basins; the application of hydrological physical models becomes more complicated. Therefore, the use of a statistical or conceptual model may be better utilised, which loses in precision but gains in the amount and size of basins that can be considered. According to De Lucena et al. (2009), the decisive criterion to select the hydrological model depends on the size and geographical dispersion of the hydropower system. It should be noted that, unlike studies of hydrological impacts, where the different components of the hydrological cycle are the object of final study; climate change impact studies on hydroelectric systems are focused on energy. Thus, a good fit of the model and the production of results that can be applied to the energy modelling is more important than to describe in detail the local hydrological cycle. Ultimately, the energy model itself, its characteristics and its data requirements are crucial factors in choosing the hydrological model.

Historic inflow values provided by the Ecuadorian power grid operator (CENACE), which were used to assess the performance of the hydrological model, may be subject to human or instrumental error. CENACE uses only one gauging station per hydropower station instead of multiple ones. This does not allow to perform a convergence analysis for inflow data. Historic inflow data uncertainty can only be overcome by better on-site measurements with more gauging stations that comply with international standards and are periodically calibrated and validated, such as the quality tests suggested by the Global Runoff Data Centre (GRDC, 2016).

Regarding temperature and precipitation datasets from the University of Anglia Climate Research Unit (CRU), it must be mentioned that these are only approximations based on the interpolation of data from disperse weather stations in the region (only seven identified for Ecuador), whose data may contain discontinuities or be poorly calibrated (Harris et al., 2014). Reliance on historic hydroclimatic data from the CRU and future climate data from KNMI may also result in incorrect information for regions with complex topography where there are sharp changes in rainfall and runoff over short distances, such as for the Tropical Andes (Buytaert et al., 2009). Derived potential evapotranspiration values computed by CRU using the Penman-Monteith approach also bring an additional uncertainty source; however, using a more advanced method would not have necessarily helped to reduce uncertainty since it would have depended on other variables provided by the same CRU dataset.

The use of the delta method to estimate the percentage changes of climate variables compared to a historic baseline entails assumptions about the nature of these changes, including a lack of variability of spatial patters (Roy et al., 2010). The lack of meteorological data and high variability of the climate system in the Tropical Andes region complicate the use of more complex downscaling methods (Buytaert et al., 2010) and using downscaled information can be no more reliable than the climate model simulation that underlies it. As stated by Taylor et al. (2012) – *more detail does not automatically imply better information*. However, future development of Regional Climate Models (RCMs) for the Tropical Andes and South America in general would help refine the calculations at the basin level. Structural uncertainty associated with the hydrological model could not be assessed, since only one model was developed in this study. The analysis of structural uncertainty of several hydrological model applied to the Tropical Andes could be a future area of research.

It is also mentioned that *ceteris paribus* was assumed in this study in terms of other hydrological variables e.g. land use and vegetation cover. The change of these variables can cause erosion and consequently alter sedimentation processes, which can substantially affect the operation and life-span of hydroelectric dams. Sediment entrapment within reservoirs, has been shown to gradually decline storage capacity and hence power production over the years (Wisser et al., 2013). The use of an additional model, e.g. a semi-distributed model (Ho et al., 2015), would allow inter-comparison of hydrological models and also include hydrological parameters such as sediment yield and land-use change in an explicit manner. All such aspects should be considered in order to draft a compelling and comprehensive study of the greater implication of water resource management on hydropower generation; this is also recognised as an area for further research. However, for the case of Ecuador, most of the assessed capacity and future hydropower potential in Ecuador are on the eastern slopes of the Andes facing the Amazon flood plain (Figure 3.11 on page 125) where currently less than 4% of the country's population lives meaning that unregulated river flow would remain as such in this region (INEC, 2017).

5.2.2.2 *Hydropower simulation*

In this analysis, we have simulated the output of hydropower stations in isolation and considered that they work at maximum capacity when water is available. However, the operation of dams and hydropower stations depend not only on the availability of water but also on the interaction with the rest of the power system and other water demanding sectors that can affect runoff in the long-term, e.g. upstream water use for agricultural or industrial purposes. System-wide impact studies that assess the nexus of water not only with energy, but with agricultural and industrial demands are of interest in regions that still have growing populations and ambitions for heavy industrialisation. The study of Spalding-Fecher et al. (2017) on the impact of climate change on hydropower in the Zambezi river basin, gives likely importance to the water model (WEAP) to characterise future water demands as to the energy system model (LEAP) used to estimate the increase or decrease in hydropower production. Similarly, the study of van der Zwaan et al. (2018) assesses the prospects of hydropower for Ethiopia from two perspectives: energy (TIAM-ECN energy model) and hydrology (RIBASIM model), looking for convergence between water demand and ambitious hydropower expansion plans in Ethiopia. Future work could similarly endeavour in soft-linking TIMES-EC with a more advanced hydrological model that captures not only hydrology but future water demands and management from other sectors.

The calculation of availability factors, which were derived from the results of the hydropower simulation model are the key inputs to characterise the operation of hydropower plants under different climate scenarios in TIMES-EC (Table 4.5 on page 194). These availability factors were calculated by simulating Ecuador's ten largest hydropower stations (see Table 3.1 on page 104), and assessing their sensibility to changes in runoff. It was assumed that the availability factors of these largest systems are representative for other existing hydropower systems and in general represent the expected availability of future deployments in each corresponding river basin. However, assuming that the operation of future hydropower projects would emulate the operation of existing ones, was a necessary rougher assumption due to the uncertainty around the definitive size of new projects, their entry date and how these new developments might operate. This assumption was necessary given the lack of information regarding future hydropower systems in Ecuador.

The availability factors obtained with the hydropower simulation model were given for different climate scenarios. According to the CMIP5 projections, all GCM results are equiprobable and therefore the occurrence of a Dry scenario is as likely as the others. Even if, on average, the hydropower system is able to offer a greater amount of energy in the NoCC, Mean and Wet scenarios, its design should consider the occurrence of a critical Dry hydrological scenario. In addition, although in the operation of the system it is possible to perform actions aimed at adaptation (such as reservoir management, energy transmission between subsystems and thermoelectric complementation), the power system depends firstly on a robust electrical system, which implies an installed capacity that minimises the probability of occurrence of deficits. Long-term expansion planning of the power sector and climate change impact studies should pay special care to the GCMs selected under what concentration scenario and make sure that both positive and negative precipitation trends are assessed, despite what the ensemble mean indicated of the region or the country.

Complimentary future research of extreme events regarding changes in frequency, intensity and duration of water cycles is also suggested to be included in not only hydropower energy modelling but hydropower infrastructure modelling. El Niño Southern Oscillation (ENSO) (Ward et al., 2014), which has large impacts in this region, could help to define a better picture of vulnerability hotspots where hydropower and other renewable energy sources are critically exposed to inter-annual climate variability. The study of Yi Ng et al. (2017) assessed the influence of ENSO on global hydropower production with an *ex-post* analysis of 1,593 power plants. Their results showed that more than one third of simulated dams exhibit statistically significant annual energy production anomalies in at least one of the two ENSO phases of El Niño and La Niña. The study of disruptive extreme events, however, has an inherently different approach to the one studied in this thesis, in which relatively consistent long-term trends are analysed. The analysis of disruptive events, e.g. the catastrophic consequences of flooding and droughts, needs a short-term analysis with shorter time-slices that allow to assess how the energy system reacts to sudden intra-annual events. Future research could combine both long-term climate trends analysis with a selection of scenarios in which extreme events disrupt the availability of hydropower generation.

5.3 modelling of the power sector in energy system optimisation models

The results obtained with the TIMES-EC model indicate that the least-cost configuration of the power system depends on the availability of hydropower subject to climate occurrence, the long-term policy and the level of risk included in the analysis. For the case of restrictions to hydropower deployment (Constrain Hydropower and Environment Priority policy cases), this would lead to the need for a higher installed capacity based on other sources, notably natural gas, but also geothermal, biomass and PV generation. On the other hand, if full hydropower potential is available (Boost Hydropower policy case), some part of the additional capacity installed (mostly natural gas) to buffer hydropower ROR variability would be idle part of the time, being used only in critical hydrological moments (see Figure 4.13 on page 200). In the next paragraphs we discuss the implications that the uptake of different generation technologies has within the limitations of their representation in TIMES-EC.

5.3.1 *The complementarities of hydropower with intermittent PV and wind*

The results of TIMES-EC show that solar PV and on-shore wind could be important technologies to obtain a low emission matrix (Environment Priority case, Figure 4.13 on page 200) and also a low risk one (Risk averse scenarios, Figure 4.31 on page 227). However, we note that a limitation of our study is the time-scale resolution used in TIMES-EC (see the time slices definition in Section 3.2.4 on page 119). This has two implications for the results: i) the value of intermittent renewable energy such as solar PV and wind could be overestimated, and ii) the full value of reservoir hydropower flexibility is not captured and therefore its complementarity with these intermittent renewables is underestimated.

An increased share of intermittent renewables will cause hydropower assets to move into an intermediate or peaking role, and create new dynamics for the operation and short-term planning of a power system that seeks to benefit from the complementarities between hydro and intermittent renewables generation. It is likely that these plants, particularly hydropower with reservoir, will need to cycle (ramp up/down and start-up/shut-down) more frequently. However, the potential for the existing hydropower assets in Ecuador to operate in this fashion is likely to be varied. A recent analyses carried out by da Cunha Saporta (2017) regarding the flexibility of hydropower plants with dams in the Brazilian context, has concluded that reservoir hydropower's high theoretical flexibility is constrained by the several other uses of water (fish hatchery, transport by river, recreation, flood control, etc.) and by the operation of hydropower plants in cascade mode. This poses the question of – *How flexible reservoir hydropower really is?*

A combination of different availability factors has been used to characterise the value of inter-seasonal storage capacity of reservoir hydropower (see Section 3.2.5 on page 124), however the representation at the intra-day time scale might be limited (morning, day and peak). A finer time scale resolution at the hourly level might show an increasing amount of reservoir hydropower deployment necessary to cover instantaneous peak demand and to provide the required flexibility to compensate for the intermittency of variable renewable energy generation. However this comes at an increasing computational effort and time in the model runs. This warrants further analysis of the Ecuadorian power system with operational and dispatch models linked to long-term modelling exercises (soft-linking), particularly for the cases of drier climate scenarios (see examples of soft-linking studies: Deane et al. 2012; Soria et al. 2016; Fichter et al. 2017).

Soria et al. (2016) discussed on what is the appropriate level of detail in the representation of the power system and the trade-off between simplicity (in an energy system model – MESSAGE) and complexity (dispatch model – REMIX). They argue that if the objective is to ensure consistency and reliability between optimal capacity expansion and optimal power system dispatch, then soft-linking expansion with dispatch models is a good option that does not increase computational effort too much (in comparison to hard-link model coupling). On the other hand, if the objective is to plan the long-term capacity expansion of the power system and to understand its impacts on the entire energy system, then a reasonable representation of the power system within the energy system model is sufficient. Thus, considering that the latter is the objective of this thesis, it is believed that the applied methodology and the time slice resolution to represent the Ecuadorian power system in TIMES-EC is adequate.

In TIMES-EC, six river basins have been depicted to capture electricity generation, both with regard to the potential and runoff seasonal patterns, which are quite differentiated throughout the Ecuadorian territory (see Figure 3.11 on page 125 and Figure 3.13 on page 127). This has highlighted which regions would be responsible for hydropower generation in the future, and gives an idea where transmission systems would need to be expanded. The regional differences in the impacts of climate change on hydroelectric generation means that a greater integration of the Ecuadorian electrical system would be necessary, allowing a greater energy trade between different regions of the country. This would also need to include an analysis of the regions in the country in which future solar PV, wind, biomass and geothermal potential is available and is likely to be deployed.

The results of TIMES-EC do not include transmission constraints, which if considered, might considerably reduce the firm and average energy of the system as a whole. Thus, a further enhancement to the model would be to explicitly represent the national grid (SNI) as to assess the future investment in the country's transmission capacity to benefit from further electricity exchanges between regions and complementarity of multiple renewable energy resources. Just as hydropower producing basins were represented, non-hydro renewable energy producing regions would bring additional geo-spatial detail to the model. However, given that in Ecuador there is effectively only one transmission system, which integrates all generation sources, having a single-region model is considered to be a valid assumption.

It is also mentioned that climate change can affect solar PV and wind technologies, however this thesis has not considered their vulnerability to climate change. This has to implications for the results: (1) Climate related uncertainties are at the core of the thesis and assuming that a range of technologies do not suffer from such uncertainties makes them "risk free" alternatives in this context (when in reality they are not). This, in turn, affects the role they would play in an optimised portfolio of energy technologies put together to hedge against the climate related uncertainties targeted at hydro; and (2) In many places the integrated nature of the assessment presented in this thesis is emphasised. Looking at the integrated system does not, however, imply in this case the integration of uncertainties related to climate. This weakens the benefits that one can draw from doing the assessment in an integrated fashion. Regarding the first implication, it has been considered that the shorter technical life-spans of solar PV and wind energy allow them to be more adaptable and "relocatable" towards the impacts of a changing climate. As to compared to a long-lived hydropower stations that will remain fixed in its position for centuries. And regarding the second point, although an integrated energy model is used, the focus of this study is hydropower and how to better represent it within the context of an energy system model. Therefore impacts and the sensitivity of hydropower to these impacts will drive the results, while excluding other technologies that could also be considered in detail and could impact results in another way. This could only be assessed by studying the other technologies in detail and making the corresponding conclusions.

5.3.2 *Electricity generation with biomass and geothermal for back-up capacity*

To the extent that, fossil fuel thermoelectric plants and reservoir hydropower are good options to meet load variations quickly, the other least-cost alternatives presented, especially biomass thermal electricity and geothermal energy, could focus on supplying base load generation (depending on climate and policy scenario). Geothermal power generation works with a high capacity factor, not only because of its high operational inertia, but also because of the high investment costs associated with its construction. The option to generate electricity with biomass (mostly sugarcane bagasse), unlike geothermal, could allow a greater degree of operational flexibility, which favours it as an option for adapting to climate change. In addition, bioelectricity, has capital costs well below those of geothermal energy (see electricity generation costs in Table 3.11 on page 137).

In the case that biomass is considered as a valid technology to adapt to climate change uncertainty, this decision is not critical as long as flexible biomass technologies are used; such as condense-extracting steam turbine (CEST) cycles or biomass integrated-gasifier/gas turbine combined cycle (BIG/GTCC) (IRENA, 2012a). These options would allow some generation modulation by extracting steam for other industrial purposes on demand. The direct combustion of bagasse with conventional steam cycles[1] and landfill gas options with internal combustion engines that currently operate in Ecuador do not have such flexibility (see Table 3.6 on page 114). For direct combustion of bagasse generation plants, a low capacity factor is unreasonable, both from a technical and economical perspective. In this sense, the indication of TIMES-EC – which selects the biomass alternative in substitution for the lost hydroelectric power and cap of natural gas-fired generation – can be problematic if direct biomass combustion is selected.

1 The cycle currently used in Ecuador is the conventional Rankine cycle with biomass being burned (oxidised) in a high-pressure boiler to generate steam.

The production of sugarcane bagasse can also use instruments to make its availability more flexible. Again, if the critical dry scenario does not occur, there must be an alternative for the use of bagasse. There are technological options that would serve this purpose, although the integrated analysis performed in the optimisation model did not point to their economic viability. One option is hydrolysis, which allows the production of cellulosic ethanol from bagasse.[2] Cellulosic ethanol, in the case of hydrolysis, is a system that consumes the bagasse, and through a bio-refinery could make biofuel available for uses in other industries and to power the transport sector. Cellulosic biofuels are becoming a commercial reality but are still expensive (Lynd et al., 2017). This indicates that electricity generated from biomass should consider parallel industrial development, particularly of the sugar cane industry.

There is a need to verify whether the conclusions of this thesis still hold under conditions in which biomass (as has been projected) has restrictions to become an important fuel source in Ecuador's energy system. It is highlighted that the biomass resource itself could be exposed to climate change vulnerabilities due to the effects of higher temperatures and extreme hydrological conditions, such as both floods and droughts (DOE, 2015). The use of biomass for energy generation also brings with it a broader set of social and environmental concerns (Cavalett et al., 2017). Specially in dry climate scenarios, the water requirements thereof will need to be better accounted for in future studies. The Ecuadorian government has stated in its NDC that it is aware of the impact that activities in the forestry sector and appropriate management of protected areas can have on climate change. Through the National Forestry Restoration Program, Ecuador plans to restore 500,000 additional hectares until 2017 and increase this total by 100,000 hectares per year until 2025, counteracting deforestation in the country, contributing to the recuperation of the forest cover and combatting climate change (UNFCCC, 2015b). *How does the water demand associated with reforestation change the findings detailed in this thesis? How would fuel switching of large parts of the transport sector to use biofuels impact domestic water demand and irrigated agriculture in Ecuador?* Perhaps the integration of a module that considers changes in land use in TIMES-EC could be of value to address them, such as Rochedo et al. (2018) has done for a MESSAGE energy system model for Brazil. These are the sorts of questions that should be considered to be addressed in follow-up work.

2 Cellulosic ethanol is ethanol (ethyl alcohol) produced from cellulose (the stringy fibre of a plant) rather than from the plant's seeds or fruit.

5.3.3 *The role of natural gas*

Natural gas plays a predominant role in all power sector configurations assessed with TIMES-EC, given that it can power flexible open cycle gas turbines (OCGT) and combined cycle gas turbines (CCGT). OCGT and CCGT have relatively low investment costs compared to other technologies and these have been modelled by assigning them high capacity credit values, to ensure their availability to cover peak demand (see Table 3.11 on page 137 for details on capacity credits).

As observed from the results, gas-fired thermoelectric capacity would be needed as a back-up option in Dry scenarios. In Ecuador, natural gas exploration activities have (yet) not found significant resources and the country does not have regasification facilities (OPEC, 2017; MICSE, 2016a). Natural gas would be necessary not only supply the power sector, but the new industrial objectives of the country (Table 3.22 on page 157). Therefore, there would likely be a need to invest in regasification and gas transport infrastructure to guarantee the supply of liquefied natural gas for electric generation and other sectors of consumption.

In spite of the operational flexibility provided by gas-fired thermal plants, the non-occurrence of critical demand periods implies not using the gas contracted for electricity generation. To the extent that reservoir hydropower with monthly storage capacity allows some degree for reducing generation in favour of previously contracted thermal generation, storing water to burn gas is not the optimal economic situation for the power sector (nor for lowering emissions). Therefore, a secondary market for natural gas would be needed where gas-fired thermoelectric plants can pass on natural gas to the industrial sector when hydrological conditions do not indicate for their economic dispatch. This would require creating operational conditions by encouraging the installation of bi-fuel burners in the industrial sector, enabling free substitution between natural gas and other energy sources, for example fuel oil, according to the conditions of the electrical system. TIMES-EC has allowed industrial thermal energy conversion technologies (direct heat and process steam, Table 3.13 on page 141) to have certain degree of freedom for fuel switching, but further research is needed to assess the limits of fuel switching in the industrial sector, particularly in the energy intensive strategic industries planned for the near future.

While according to the results a foreseeable decarbonisation of the power sector is possible with the uptake of hydropower, bioelectricity and solar PV, Ecuador's overall energy mix would still be highly dependent on crude oil and petroleum products in 2050 (see Figure 4.23 on page 216 and Figure 4.42 on page 244). In this sense, and within the context of more radical transitions to achieve emission reductions at a global scale, further research could study what the deep decarbonisation of the whole Ecuadorian energy matrix would look like, beyond the proposed NDCs and with an aim to the new revised target of reaching 1.5°C by the end of the century (van Vuuren et al., 2018).

5.3.4 *Electricity demand*

Energy demand data input to TIMES-EC relates to the expected end-use and final energy demand for different economic sectors during the modelling horizon. As new demand technologies continue to appear and consumer behaviour changes, different patterns of inter-annual and intra-day electricity consumption could derive different results. For instance, the non or partial realisation of the strategic industries projects by 2025 would alter the base-load demand requirements of the power system, especially for the continuous power demand in off-peak hours of steal and aluminium industries. The changing intra-day demand patterns would mean that other technologies could provide energy with more benefits than a hydropower dominated matrix, particularly solar PV if mid-day power demands increase. Because the power demand of the considered strategic industries is based on continuous processes (see Table 3.22 on page 157), it is assumed that there are little changes in intra-day power demand load curves that can take place outside of intensity changes – which would only imply that if the strategic industries do not materialise completely, the results for the power system could be linearly adjusted.

Demand shifting initiatives can also alter the daily load curve in order to provide convergence between electricity demand and intermittent renewable resources – either through the policies indicated in the energy efficiency plan (see Table 3.21 on page 156) or the uptake of more expensive smart appliances due to new socio-economic conditions. According to a new analysis by the International Energy Agency – *"The future of cooling"*, the growing use of air conditioners in homes and offices around the world will be one of the top drivers of global electricity demand over the next three decades (IEA, 2018). This has major implications in the context of uncertain climate change in developing countries. While roughly half of the population in Ecuador lives in the Ecuadorian highlands – where mild temperatures have halted the use of air conditioning or heating – the other half lives in the warm tropical coastal areas where air conditioning has so far only been used by upper-middle and high-income households. Increasing temperatures can increase the uptake of air conditioning in this region and even commence its uptake in the highlands. To assess daily electricity demand patterns, this study has obtained hourly electricity demand data for 2016 from the national grid operator. No representative large differences in energy consumption where found between seasons of the year or between the coastal and highlands region, therefore the same electricity demand profile pattern has been assumed for the entire modelling horizon (as discussed in Section 3.2.7 on page 138). However, further research is required to investigate how climate change and growing socio-economic conditions can impact this daily and seasonal demand profiles.

A final word on electricity and final energy demand is concerning its interaction with the NDC and future climate goals. Changes in final energy demand according to policy, risk or climate change scenario have not been representative in this research. One reason for this is that Ecuador's main strategy to reduce energy-related emissions is centred only on the power sector deploying large shares of hydropower capacity in the mid-term (2025). Future mitigation efforts that arise from future international commitments could require for the demand side sectors of the economy particularly the transport and industrial sectors to join decarobonisation efforts. Such an NDC (or whatever name future commitments take), would require greater switches from fossil fuels towards renewable electricity and from inefficient to more efficient demand side conversion technologies. This could lead to results that show greater changes in final energy and the way to really decarbonise the whole energy system of this developing country. Future research could reassess the role of hydropower with an enhanced representation of demand in the energy system model. It must also be mentioned that only one middle-of-the-road socio-economic scenario was considered – the SSP2. Choosing other socio-economic scenarios would also shape the intensitiy of end-use energy growth differently. It is suggeste research consider the SSP5 (high) and SSP4 (low) scenarios (Riahi et al., 2017).

5.4 INTEGRATING PORTFOLIO THEORY IN TIMES

This thesis provides an analysis of the least-cost future generation portfolios in Ecuador for 2050 under highly uncertain oil and natural gas prices, electricity generation infrastructure costs, and long-term climate change. A Monte Carlo-based financial Portfolio Theory approach was integrated into an energy system optimisation model (TIMES-EC) to assess expected generation costs, associated cost risk and the configuration of possible robust electricity generation portfolios.

In scenarios that seek to reduce risk, the power system moves away from run-of-river hydropower and natural gas, while reservoir hydropower, solar PV and geothermal experience an uptake (see Figure 4.31 on page 227). The modelling results also show that an oil-fired generation phase-out is a robust decision, as well as maintaining current capacity levels of natural gas up to 2050.

Results also indicate that the efficient frontier characteristics of future least-cost electricity generation portfolios depends strongly on the long-term climate change scenario that is taken into account for Ecuador (Figure 2.5 on page 77). A Dry climate change scenario has a higher risk profile for the power sector, but also has greater risk reduction potential, when compared to a long-term Wet or NoCC climate change scenario . In terms of costs, the expected average generation cost by 2050 roughly doubles when moving from a large hydro-dominated risk-neutral generation matrix to a more diversified non-hydro renewable (PV, wind, geothermal and biomass) risk-averse generation portfolio alternative.

5.4.1 *Assumptions for implementation*

To be able to implement the mathematical formulation of financial Portfolio Theory in TIMES-EC, three fundamental assumptions are implicitly made and are discussed in the following list in the context of the arguments presented by Nijs and Poncelet (2016):

1. Short-term uncertainty (i.e., uncertainty on fossil fuel prices and electricity infrastructure costs) is assumed to be recurring and therefore present over the entire modelling horizon (2017 to 2050). For the case of crude oil and natural gas, the recurring uncertainty around their prices has been an unresolved and ongoing issue in international commodity markets for decades. However, while the correlation of crude oil and natural gas prices has been assumed constant according to the historic average, it is recognised that their price correlation might change (reduce) in the mid-term helped by natural gas' low prices, ample supply, and its role in reducing air pollution and other emissions (IEA, 2017). For the case of hydropower, although the technology is over a century-old, cost overruns still occur and the uncertainty of its definitive capital cost still remains (as discussed in Section 3.3.2 on page 167). For PV and wind technologies, although they show lower uncertainty ranges for their capital cost, uncertainty regarding their long-term cost reduction is still significant for the long-term.

2. It is assumed that there is path dependency over time between values of the uncertain parameter (e.g. crude oil price in year $t+1$ are assumed to be dependent from the average crude oil price in year t). This is one of the key assumptions when a GBM model is used, as detailed in Section 3.3.2.1 on page 167. In other words,

this means that – if price in 2030 is $100 per barrel, it is more likely to be $120 per barrel in 2040 in this run than in a run in which price simulation would lead to $10 per barrel in 2030. This is a drawback of GBM in the sense that oil and gas prices often show jumps caused by unpredictable events or news that are unrelated to the immediate past, in GBM there a continuous path dependency (no discontinuities). However, GBM has been used together with Monte Carlo sampling to go beyond a single price path, and rather have a look at the uncertainty space that oil and gas prices could have based on their historic volatility trends. This uncertainty space is what the model captures as a measure of risk and procures to move away from technologies that use fossil fuel prices that consume fuels with a large uncertainty space.

3. Operational decision variables are assumed non-adaptive or non-recoursive. As a consequence, cost risk (i.e. *UpAbsDev* cost, detailed in Section 3.3.1 on page 160) is actually an upper limit for the average positive deviation of system costs. Under this assumption, there is only one set of operational decisions needed. This means that there is a lack of operation optimisation in the model, given that in reality for example, the operator of a thermal power plant can optimise production at any given year when information about gas prices is revealed (within the flexibility that the installed capacity in place allows). The operator could actually decide to not operate at all if gas prices are extremely high. This is an important shortcoming as in reality one will make operational choices based on the actual situation. Having uncertain prices and the ability to have recoursive action opens the way for financial *real options* (Martínez Ceseña et al., 2013), which could be modelled with stochastic approaches (Seljom and Tomasgard, 2015). However, while in reality, the real option to optimise production based on fuel price information can happen many times during a long period of time, stochastic approaches in energy system models are still limited by the number of states-of-the-world they can represent.

5.4.2 *Price and costs uncertainties*

The uncertainties of fossil fuel prices and electricity infrastructure investment costs have been characterised with normal probability distributions based on historic data sets. However, this characterisation may not be the only valid view, and might vary if different cost probability distributions are applied. For example, Pye et al. (2015) use triangular probability distributions to systematically rank uncertainty of fuel prices and technology costs in an energy model for the UK and Callegari et al. (2018) use log-normal distributions to project cost-overruns of large hydropower infrastructure (>1, 000 MW) in Brazil. Future work would benefit from inter-comparison studies that use different statistical measures of risk, as the ones mentioned, and its subsequent impact on the results obtained with a least-cost energy system model.

The recurring uncertainty that was defined for the capital costs of hydropower is significantly larger (average cost overrun of 70.6%) compared to other generation technologies (Figure 4.29 on page 225). Some may argue that this level of capital cost uncertainty is exaggerated and that it might not correspond to the Ecuadorian context. One of the means that has been sought to consider the *"uncertainty of the uncertainty"* is to work with six scenarios of increasing levels of risk, from a scenario run that considers no risk at all (50% confidence interval) to a full consideration of the full distribution of uncertainty (99% confidence interval), instead of just working with the extreme cases. This allows to see the progressive changes that TIMES-EC performs to move the power system away from a risky generation portfolio and can suit a more varied array of decision makers which can be well in between the risk-neutral and risk-averse cases.

The price volatility of biomass or CO_2 emissions were not taken into consideration. However these prices might become of relevance in the future as efforts to tackle climate change increase. In the study of Usher and Strachan (2012), the import availability and price of biomass is identified as one of the key mid-term uncertainties in long-term decarbonisation scenarios for the UK, however it is demonstrated that fossil fuel price uncertainty is much larger. Likewise some studies have included the uncertainty of volatility of carbon prices, such as the study of Losekann et al. (2013) who use Portfolio Theory to evaluate the Brazilian generation mix expansion in three CO_2 price scenarios. Their results show that high CO_2 prices increase the share of wind and biomass in the mix, i.e. the model selects technologies that are less probable to incur in a carbon price. It is mentioned however that using Portfolio Theory to explore the uncertainty of carbon prices is extremely difficult given that there is not long enough historical data on carbon prices and their correlation with other energy commodities. The favoured approach is therefore to assess different scenarios of carbon taxes. In any case, given Ecuador's abundance of biomass resource (MEER, 2014) and an Ecuadorian climate policy which makes no mention of a carbon tax (UNFCCC, 2015b), their omission should not significantly impact the results. Future research could consider looking into these additional sources of price uncertainties.

Although only the cost deviations of fossil fuel prices and electricity infrastructure is explicitly addressed in this study, it is recognised that issues other than cost variability can have an impact on the overall risk profile of electricity supply in the long-term: The availability of credit and financing mechanisms, learning effects and disruptive new technologies, regulatory or policy risks (such as a new government enforcing a new energy and climate policy agenda), the strength of the transmission and distribution networks, and the risk of domestic social or industrial disputes (Allan et al., 2011; Masini and Menichetti, 2013). Future extensions to the portfolio approach may be able to capture some qualitative aspects of these other influences (Hadian and Madani, 2014). Alternative approaches could also move away from the quantitative approach (statistics) and enter the realm of deep uncertainty in which the influence of non-optimal actor behaviour is equally or more relevant than the uncertainties surrounding fuel prices and technology costs (Li, 2017). It could also be useful to compare/complement the Portfolio Theory approach with other quantitative methods to handle uncertainty in energy system models, such as stochastic programming (Seljom and Tomasgard, 2017) or modelling to generate alternative (Price and Keppo, 2017), which have recently been integrated into TIMES.

5.5 LIMITATIONS OF GENERALISATION

The findings of this PhD thesis can be generalised while taking into account three major limitations: geographical region, hydropower share in the power generation matrix, and capacity expansion plans based on least-cost approaches.

First, results could be only extrapolated to neighbouring countries that have similar climate characteristics – and therefore similar impacts of climate change on water resource availability. Second, the results in this thesis can be generalised to other countries in which the power system currently has or expects to have large shares of hydropower generation and given similar capital costs, operation costs, and discount rate (electricity technology costs can be consulted in Table 3.11 on page 137). TIMES-EC is a country-specific model – as it is developed based on the energy system of Ecuador – and is therefore likely to be different from any other energy system. In addition, hydropower has been particularly detailed according to basin, remaining potential, size and type – run-of-river and reservoir. The role of hydropower in the power system in TIMES-EC is dominant and changes to its output due to climate variability or policy constraints dictate the investment and operation of other complementary generation alternatives. Power systems in other countries with lower shares of hydropower and predominant thermal generation would respond differently. As a result, results are valid for energy systems with similar shares of hydropower, whereas the policy case scenarios (Section 3.2.10 on page 151) can be used as a sensitivity for different paths of long-term hydropower development.

Similarly, the risk assessment with Portfolio Theory performed to answer research question three can be generalised given that volatility of fossil fuel prices has international impacts, and infrastructure cost uncertainty was taken from a database that assesses electricity projects worldwide in both developed and developing countries (Section 3.3.2 on page 167). It was shown that cost risk and the hedging potential of non-hydro renewables depends significantly with respect to different climate change scenarios and the level of risk that is considered (from risk-neutral to risk-averse). This again is a consequence of the large shares of hydropower in the Ecuadorian system. The increasing levels of risk (Section 3.3.3 on page 175) serve as a sensitivity analysis that should be consulted if the decision maker has different perceptions towards risk. Further, the quantitative uncertainty of cost overruns of hydropower infrastructure should be revised for countries with significant political risk or socio-environmental issues, in order to quantify a more relevant context-based risk-adjusted uncertainty range. The limitations discussed previously in this section should also be consulted before generalising results to other countries.

Inasmuch this chapter has focused on discussing the results, limitations and mentioning areas for future work. The following chapter summarises the findings along with the original contributions of this research and implication for policy.

Part IV

CONCLUSIONS

6

CONCLUSIONS

This concluding chapter summarises the findings of each research question along with the main contributions to knowledge of this PhD thesis. This chapter also includes a set of implications for policy making regarding hydropower deployment.

6.1 RESTATEMENT OF THE RESEARCH QUESTIONS

At the time this PhD research was started, an upsurge in hydropower development was underway in developing regions (WEC, 2015a), namely Africa, South East Asia and South America. The abundance of financing, fast growing electricity demands, resource availability and the efforts to decarbonise the power sector, seemed the perfect justification for the implementation of economically beneficial hydropower systems. After carrying out a research contextualisation in the Introduction on page 3 and a literature review in Chapter 2 on page 23, it appears that regarding power sector planning with energy system optimisation models, hydropower has three significant uncertainties to deal with:

1. The uncertainty of climate change on long-term hydropower generation

2. The impact of hydropower variability on the long-term overall power system; and

3. The uncertainty of hydropower's capital costs

These research problems presented in this thesis were assessed with an innovative modelling approach that combines engineering (technology explicit), economics (cost optimisation), and finance (portfolio theory) models, in order to investigate these issues from multiple and interconnecting perspectives. This PhD research applied the presented methodology in a case study for the Republic of Ecuador's energy system until 2050. The main findings are summarised as follow.

6.2 MAIN RESEARCH FINDINGS

This thesis has presented a methodological approach to assess the role that hydropower could play in the energy system under the uncertain impacts of climate change, policy and costs. This approach is based on a series of models, that starts with climatic projections correspondent to GHG concentration scenarios, followed by a process of downscaling and forcing a hydrological model to obtain changes in seasonal inflow into hydropower stations. Subsequently, these changes in inflow are fed into a hydropower plant simulation model to obtain availability factors under different climate scenarios. These factors are then used in an integrated energy system optimisation model to assess least-cost adaptation options for power generation according to the projected impacts of hydropower generation and different energy policies for hydropower deployment. Finally, a financial Portfolio Theory feature is integrated into the energy system optimisation model to assess the impact of volatile fossil fuel prices and electricity generation infrastructure investment cost on the least-cost generation portfolio.

This section summarises the main findings of the research as a whole. Below are the main findings of the research, grouped by research question.

6.2.1 *The long-term impact of climate change on Ecuador's hydropower generation*

Research question one read: *"How will seasonal and annual inflow into the largest hydropower stations in Ecuador change over this century according to climate change projections?"* Future projections of hydroclimatic variables for six hydropower producing river basins in Ecuador were downloaded according to 40 GCMs of the CMIP5 ensemble for the RCP2.6, RCP4.5 and RCP8.5 concentration scenarios. A hybrid hydrological model was used in which annual inflow was modelled by a conceptual water balancing method and monthly variability was modelled with a statistical method. This hybrid model was shown to be effective in contouring the limitations related to the lack of data, and can be an interesting alternative to purely data-intensive physical hydrological models.

Subsequently, a hydropower operation model was used to estimate generation from future inflow projections in Ecuador's main hydropower stations. This model allows to calculate, for a set of inflow series and technical characteristics, the monthly availability factor of a hydropower plant. The model has the ability to simulate individual or aggregated hydropower plants in a cascading layout.

The following findings were identified in Chapter 4 in Section 4.1 on page 181:

- The largest source of uncertainty in long-term climate change impact studies on water resources are the differences among individual climate projections (GCMs). In comparison, differences among concentration scenarios – i.e. the RCP2.6, RCP4.5 and RCP8.5 were found to be much smaller compared to the difference among individual GCMs. Performing an uncertainty analysis for the three RCPs adds little information, while assessing individual GCMs under a single RCP allows to characterise a broader uncertainty space of the possible effects of climate change on water resources.

- Using climate model ensemble mean values (e.g. the mean of the CMIP5 ensemble for the RCP4.5 scenario) in climate impact assessment studies masks large disagreement among the GCMs of the ensemble. Differences for projected annual inflow into Ecuador's largest hydropower stations were found to be large depending on GCM used. Deviations from the annual mean historical inflow towards the end of the century span from -82% to +277% (see Figure 4.5 on page 188). From 40 GCMs used in this thesis, 22 GCMs project an increase in runoff, while 18 GCMs project a decrease, therefore the mean of results for the ensemble shows an effective increase in annual runoff. However it must be remembered that all GCMs from an ensemble are considered to be equiprobable and therefore the ensemble mean does not entail a higher probability of occurrence. Wet and dry scenarios or GCMs that project both increases and decreases of precipitation should be preferably used in climate change impact studies on water resources and hydropower generation.

- GCM projections data at the monthly level has been made available until the end of the century and give information on seasonal changes in hydroclimatic variables (see the database of KNMI). When using the CMIP5 ensemble projections to characterise the probability space of hydroclimatic variables, the assessment of the seasonal patterns indicates that Ecuador has larger uncertainty for the wet months compared to dry months. On a monthly basis there is an average decline of precipitation from 100 mm to close to 0 mm for the dry season compared to an increase from 300 to a maximum 800 mm in the wet season (Figure 4.2 on page 186). Studies that look to assess hydropower generation in the future, should use climate data at least at the monthly level.

- The scale of climate change impact on hydropower depends on technology type. Hydropower stations with storage capabilities show less sensitivity to inflow changes compared to runoff facilities. Reservoir-based hydropower could have certain climate change risk control advantage compared to run-of-river stations; however, extreme dry scenarios could leave any storage capacities ineffective. The changes in hydropower output due to climate change are not symmetrical for equiprobable wet or dry climate change scenarios. Windfall energy production due to the occurrence of a wet scenario is limited by the fixed installed capacity of the hydropower station, therefore large spillage would be expected. On the other hand, dry scenarios can force both run-of-river and reservoir hydropower stations to reach zero production for continuous months. Annual hydropower generation in the largest hydropower stations in Ecuador has been compared for different climate change scenarios and historic generation. Results show that the historic (1971-2000) average annual availability factor of the Ecuadorian hydropower system is 57%, a scenario that considers the RCP4.5 ensemble mean of the CMIP5 by 2050 would increase the availability factor to 58%, while a Wet scenario (+1 SD of the CMIP5 ensemble) would increase it to 67% and a Dry scenario (-1 SD of the CMIP5 ensemble) would reduce it to 43%. (see Figure 4.9 on page 194 and Table 4.5 on page 194)

6.2.2 *Least-cost climate change adaptation options for Ecuador's power sector*

Research question two read: *"How does hydropower output variations due to climate change impact the long-term least-cost power system development pathway of Ecuador by 2050?"* or in other words – *How can the power sector adapt at the minimum cost to the variability of hydropower in the long-term?* Therefore, an integrated energy system optimisation model for Ecuador (TIMES-EC) was developed to depict the power sector and assess least-cost adaptation options according to hydropower availability scenarios and policy cases until 2050. The availability factors for representative hydropower stations under different climate change scenarios obtained in research question one were used as input into (TIMES-EC). The following key findings were identified in Chapter 4 in Section 4.2 on page 198:

- Electricity demand increases between 58 – 68 TWh in 2050, which amounts to a threefold increase compared to current levels (23 TWh in 2017). Electricity demand will be dominated by the industrial sector and energy-intensive strategic industries that are part of Ecuador's economic development plan, the residential sector follows driven by the shift of demand services such as cooking and water heating from LPG to electricity (Figure 4.21 on page 213).

- Total final energy demand reaches 1,200 PJ in 2050, compared to 574 PJ in 2017 and is dominated by the transport and industrial sectors. According to the TIMES-EC model, Ecuador would supply most of its final energy demand with oil products (800 PJ), followed by electricity (200 PJ), gas (150 PJ) and biomass (50 PJ). Ecuador currently does not have significant natural gas reserves and would need to open its energy matrix to imports of LNG, with the corresponding implications for its energy security. This can be seen in Figure 4.23 on page 216.

- To supply electricity demand, total installed electricity generation capacity in Ecuador could increase by 15 – 18 GW by 2050, which amounts up to a threefold increase compared to current levels (7.5 GW in 2017). Whereas the current portfolio is a hydrothermal one dominated by large scale hydropower generation, the model shows that the future could hold a number of different options according to the policy case and climate scenario outcomes that may transpire. This can be seen in Figure 4.13 on page 200. Electricity generation will need to increase by 70 – 78 TWh/y by 2050, which is up to a fourfold increase compared to current levels (24.5 TWh in 2017).

- Hydropower will remain as one of the most cost-effective and low emission technologies in the Ecuadorian power sector in the long-term. However, constraints on deployment and uncertainty around climate change impacts could hinder its ability to contribute to supply electricity demand, the fulfilment of NDC targets and maintain low power system costs. Across the climate change scenarios and policy cases, hydropower installed capacity ranges from 5–12 GW by 2050 and its share in total generation varies significantly from 29% (constrained large hydro + dry climate scenario) to 86% (strong hydro deployment + wet climate scenario) (Figure 4.18 on page 204).

- Extensive deployment of hydropower only occurs when large-scale hydropower potential in the Amazon can be tapped and hydropower deployment is forced in the model according to government plans. The extensive deployment of hydropower, displaces all other non-hydro renewables from the system. Even with large hydropower capacity installed, significant shares of natural gas-fired generation must be deployed to supply the system during the dry periods between October and January (Figure 4.14 on page 201). Restricting the deployment of large hydropower has a potential lock-in for a gas-fired dominated system. In the occurrence of a dry climate scenario, almost half of the generation in 2050 (> 70%) could come from gas.

- Ecuador can achieve its implied power sector NDC level until 2050 (53 GtonCO_2e) without the need of deploying large (>450 MW) hydropower capacity. Biomass generation, geothermal combined with small and medium hydropower is key to achieve the NDC when both emissions and large hydro deployment are capped (see Figure 4.13 on page 200). Wind and solar PV also contribute but in smaller shares. However, this solution doubles average generation cost (6 to 12 US¢/kWh) depending on the price of biomass resources and technology, as can be seen in Figure 4.19 on page 210. No carbon capture and storage (CCS) technologies are detected in the results, despite being available for the model to choose. In addition, an energy policy focused on deploying large-scale hydropower proves to be the most capital-intensive option (cumulative investment 2017-2050 ~US$ 65 billion), while a diversified power matrix with non-hydro renewables and small/medium hydro is less capital intensive (~US$ 50 billion).

6.2.3 *Integrating recurring uncertainties in an energy system model*

Research question three read: *"How does incorporating recurring uncertainties such as the volatility of fossil fuel prices and the capital cost of electricity infrastructure impact the investment portfolio for the power sector?"* Energy modelling is subject to the underlying technical-economic assumptions of the analysed technologies, which may vary over time and can alter the suggested least-cost configuration of the energy system. A financial Portfolio Theory approach was integrated into the TIMES-EC model to assess the impact that the volatility of fossil fuel prices and electricity generation technology costs has in the optimisation process. The following key findings were identified in Chapter 4 in Section 4.3 on page 220:

- Financial Portfolio Theory applied to the power sector allows to model the trade-off between cost and cost-risk of generation portfolios (efficient frontier). The reduction of portfolio cost risk translates into investment and operational decisions that seek to deploy larger shares of technologies that have lower inherent cost-risk. However, reducing risk has an impact on the system generation cost, thus the risk level consideration in the model will depend on the risk characteristics of the decision maker – risk neutral or risk averse. Results show that for Ecuador, the trade-off between cost and cost risk by 2050 depends strongly on the climate change scenario that is taken into account and that expected average generation cost increases in the Wet climate scenario from 4 to 8.5 US¢/kWh, while for the Dry scenario it increases from 4 to 12.5 US¢/kWh when moving from a risk-neutral to risk-averse generation portfolio. This can be see Figure 4.35 on page 233 where the efficient frontier has been shown.

- To hedge against cost risk, TIMES-EC suggests that the generation portfolio should move away from oil/gas-fired thermal generation and ROR hydropower, towards a more diversified system configuration with larger shares of reservoir hydropower, geothermal and solar PV. It was shown that even considering the large uncertainty of hydropower capital costs, this technology maintains an important capacity share (>50%) in all assessed scenarios by 2050, although there is a negative correlation between the deployment of run-of-river and reservoir hydro. Run-of-river hydropower installed capacity ranges broadly (5–12 GW by 2050) with lower shares considered to be favourable for a risk averse portfolio, however the model suggests that higher shares of reservoir hydro should be taken into consideration for risk reduction, although in a smaller range (2.5–5 GW). This can be seen in Figure 4.31 on page 227 and Figure 4.32 on page 228.
- Uptake of non-hydro renewables are considered as a way of hedging the power system against risk. The share of non-hydro renewables introduced into the generation matrix to reduce risk depends on the climate scenario. Non-hydro renewables reach a maximum of 25% of generation share in the Dry climate scenario, while only a 10% share in the Wet climate scenario. PV is particularly important for risk hedging in the Dry scenario, where it reaches installed capacities of 4 GW. Geothermal is suggested to be deployed at its maximum potential (0.9 GW) and wind also should be deployed (1 GW) by 2050. Biomass generation is only considered to be good for risk hedging for low levels of risk consideration and the model suggest a total phase out of oil-fired capacity (Figure 4.38 on page 237).
- Emission levels for risk hedging scenarios are lower than the Ecuadorian implied NDC level for the power sector (cumulative of 53 GtonCO_2e between 2017-2050). Given that hydropower maintains a large share of generation, all scenarios show lower cumulative emissions than the NDC level, except for the risk-neutral cases in which gas-fired generation has larger shares. In a risk-neutral + dry scenario, a gas-fired dominated power system would be the least-cost alternative which would cause a five fold increase over the NDC level (250 GtonCO_2e) (Figure 4.43 on page 245).

- Electricity and final energy demand react to the consideration of risk in the model due to the change of power supply prices. Electricity demand decreases from 75 TWh to 65 TWh in 2050 as the system moves from risk neutral to risk averse. Given that a risk averse system implies higher generation costs, the energy system shifts away from electricity towards petroleum products, particularly in the industrial sector (heating processes) and the residential sector (cooking and water heating) (Figure 4.40). Moving away from electricity towards less efficient petroleum products has a negative impact in final energy demand, which increases in 30 PJ when moving from risk neutral to risk averse. It must be mentioned that capital cost risk was only considered for electricity generation technologies. Including risk characteristics in other elements of the energy sector can have other implications for final energy demand.

6.3 ORIGINALITY AND CONTRIBUTION

Based on the research questions and the literature review,[1] the contributions of this thesis can be classified in three major areas:

1. Use of large ensembles of long-term climate change projections,
2. Depicting hydropower in an energy system model of a hydro-dominated power system, and
3. Combination of Portfolio Theory with an energy system optimisation model.

The justification for each contribution is provided in the following paragraphs.

6.3.1 *Contribution 1: Use of large ensembles of long-term climate change projections*

Past studies have consistently stated that one of the greatest uncertainties surrounding climate change impact assessments is the large disagreements among GCM projections, particularly in relation to the magnitude and sign of change of long-term precipitation (Escobar et al., 2011; Kundzewicz et al., 2018; Bates et al., 2008; Ho et al., 2015). The latest AR5 report of the IPCC (Cisneros et al., 2014; IPCC, 2014a) insists on the importance of considering uncertainties surrounding climate in supporting national adaptation and mitigation strategies, and recognises the lack of consistent tools to deal with these

1 Research gaps found in the literature were discussed in Section 2.4 on page 86.

uncertainties. In this context, there are a number of novelties in this research worth noting.

Firstly, whereas past climate change impact studies focusing on hydropower have used a combination of a few GCMs and emission/concentration scenarios (see Table 2.6 on page 59), this work assesses a large ensemble of 40 GCMs to characterise the long-term monthly runoff availability for hydropower generation in individual Ecuadorian river basins across a comprehensive range (as detailed in Section 3.1.3 on page 99). This allows for a much more granular level of spatial (basin level) and temporal (monthly) resolution in the energy model than has been possible in previous studies, and a more rigorous representation of climate change uncertainty. Although from the whole ensemble of GCMs, only three realisations have been extracted (wet, dry and mean), these realisations are informed by the full range of GCM projections. This matters because it uses the range of uncertainty that climate modellers are providing to inform the uncertainty of the water resource availability in the future for the energy model.

Second, this thesis has taken one step forward in depicting hydropower inter-annual seasonality at the monthly level making direct use of monthly GCM projections already available for the end of the century. This contrasts with other recent studies that use energy system optimisation models and depict hydropower only at the quarterly level (spring, summer, autumn and winter), e.g. Teotonio et al. (2017) for Portugal, Seljom and Tomasgard (2015) for Denmark and Kannan and Turton (2014) for Switzerland. The monthly resolution used in this study allows to capture high and (critical) low flow months that would be blurred out if only a seasonal (three or six-month resolution) would have been used.

Thirdly, the study uses a simple conceptual/statistical hydrological model that is not data intensive, which can be replicated in data scarce regions that are considering large deployment of hydropower infrastructure. The novelty of this approach is that is uses hydrological model used historic and future hydroclimatic data made available online by the University of East Anglia Climate Research Unit (CRU) and the Royal Dutch Meteorological Institute (KNMI). This approach makes the method transparent and replicable and easy to adopt for other countries or regions looking into how to model the prospective changes of water resources using online hydrometeorological data.

Finally, the uncertainty of the impacts of climate change upon the Tropical Andes has not been systematically investigated, despite the importance for hydropower deployment for the region (Finer and Jenkins, 2012b; Buytaert et al., 2011). Therefore this study adds to the literature of developing regions which are envisioning rapid economic and energy growth, and are contemplating the deployment of large hydropower systems as a cheap and reliable solution for the long-term. This work brings insights regarding the vulnerability of hydropower to climate change and what alternatives to power generation should be further paid attention for more robust power systems in the long-term.

6.3.2 *Contribution 2: Modelling hydropower in energy system models – a case study for Ecuador*

This thesis showcases the first application of the energy system optimisation model TIMES (Loulou and Labriet, 2008), to develop a detailed long-term energy system assessment for the Republic of Ecuador (TIMES-EC) until 2050. Details on the TIMES-EC model structure and assumptions were presented in Section 3.2 on page 110, where hydropower was assessed in detail due to the particular importance of hydropower in Ecuador's power sector and its relevance for Ecuador's NDC contribution to the Paris Agreement. Using an energy system optimisation model adds significant value by representing not only the impacts of climate change on hydropower electricity generation, but also the way in which the whole energy system adapts in a least-cost manner to new conditions.

The majority of previous studies in this area have mostly used hydropower electricity simulation models in isolation from the rest of the energy system, and the ones that use energy system models, do so for developed countries, as was discussed in Section 2.2.2 on page 46 (see also Table 2.6 on page 59). While these studies have been used as a reference, it is noted that the power systems in developed countries have already tapped most of their hydropower potential or their energy demand has reached a saturation point for which new large capacity additions of hydropower are not envisioned. This directs interest and research towards developing and emerging economies that have still large untapped hydropower resources and are planning to rely intensively on hydropower infrastructure. This thesis builds on the the literature that is growing to inform these countries about their hydropower-dominated future. Implications for policy will be expanded further below in Section 6.4.

In addition, this thesis has not only assessed the impact that climate change can have on hydropower generation, but how different long-term hydropower development polices can impact the system as well. Most studies usually have assessed either climate change or policy developments. TIMES-EC has allowed to assess these two distinct levels of uncertainties simultaneously with an integrated scenario approach that broadens the analysis of the possibilities of hydropower future role in the power system's configuration. The policies presented in this thesis are relevant for countries relying on hydropower deployment to meet economic and climate targets.

6.3.3 *Contribution 3: Combination of portfolio theory with an energy system optimisation model*

A number of modelling capabilities were required to undertake this research, including: hydrological modelling, simulation of the operation of hydropower systems, energy system modelling, Monte Carlo analysis, Geometric Brownian stochastic modelling and Portfolio Theory cost-risk analysis. As shown in Table 2.6 on page 59 and Table 2.8 on page 82, the full extent of these capabilities is not present in an integrated manner in previous studies. The complexities in energy system modelling require to link a series of models and approaches. Thus using the strengths of each model to improve the data input to the following model. This thesis has shown how to soft link a hydrological and hydropower simulation model, and then use those results to improve the representation of hydropower in an energy system model. While combining a set of specific things for the first time probably happens in almost every single piece of research, the combination of new tools with new data available for hydropower modelling and the enhanced representation of this specific technology in an (not new) energy system model is still of worth.

Traditionally, energy system optimisation models have not been capable to combine cost-risk (from a portfolio theory perspective) of the volatility of fossil fuel prices and uncertainty of capital cost overruns into the cost optimisation process. Furthermore, studies that have explored this applied to the power sector do it exogenously once a set of plausible energy system portfolio have been determined for a milestone year in the future (as was discussed in Section 2.3.2 on page 72). Consequently, there was a need to expand on a current energy system model in order to tackle the research question, particularly of how taking into consideration the significant cost uncertainties of large hydropower impact the least-cost solution. A TIMES energy system optimisation model was developed, which integrates thousands of simulated price and cost evolution paths into the cost optimisation decision process. The approach presented in this thesis allows the energy system model to perform the Portfolio Theory assessment endogenously and dynamically, i.e. it minimises cost and risk simultaneously while optimising the long-term investment for the power sector in each period of the modelling horizon. There are some previous studies that have endogenised a measure or risk into the objective function of and energy system optimisation model (e.g. Messner et al. 1996; Krey and

Riahi 2009), but they have only considered capital cost uncertainty of power technologies and cost overruns based on theoretical deviations, differing from the approach presented in this thesis that uses actual statistical cost overrun data from a large set of 400 power generation projects worldwide to characterise the uncertainty of generation technologies. In addition, these studies have used a Monte Carlo approach based on a GBM model to sample price and cost trends into the future. This adds to the analysis by using more complex approaches that allow an improved exploration of the uncertainty space. This expansion of an existing energy system model to integrate risk constitutes and additional contribution of this PhD thesis.

6.4 IMPLICATIONS FOR POLICY

Ecuador's move towards large hydropower over the past decade and for the foreseeable future has been justified on the grounds that it is the least-cost and low-emission alternative for power capacity expansion. From a purely energy system cost-optimisation perspective, the findings in this thesis may not give substantial reasons to oppose the ambitious plans for hydropower development in Ecuador as currently intended by national energy authorities. The partial equilibrium cost-optimisation model (TIMES-EC) shows that extensive hydropower development could meet the government's targets for economic growth (strategic industries) while maintaining average system costs and GHG emissions low. However it is also shown that in the occurrence of a dry climate scenario, hydropower could face serious shortages in the long-term and therefor alternative non-hydro low-carbon options should be considered as an insurance in the face of uncertain climate change.

According to the results presented in this thesis, hydropower would remain as an important generation source for Ecuador. The modelling activities, however, are merely based on hydrological, economic and financial approaches, and thus do not take into consideration a series of other relevant factors, such as environmental, political and social ones. Such factors may persuade Ecuadorian government officials to take a different course of action and reduce their hydropower ambitions substantially.

In this sense, important messages to policy makers are:

- Although hydropower could be considered a low-cost renewable technology, evidence shows that cost-overruns and delays have become a feature of large-scale hydropower projects and should be factored into the energy planning process. The failure to complete large energy projects has a series of knock-on effects such as:

loss of the economic justification of the project, price hikes for consumers and reducing the investment attractiveness of the country. This takes relevance, particularly in developing countries where large electricity projects are under governmental management and their failure puts a strain on nationally owned power utilities and on the national financing capacity in terms of foreign borrowing and domestic credit. Ecuador's eight hydropower government-lead flagship projects have been almost totally financed (US$ 6 billion) through oil-backed loan mechanisms with the China Development Bank and China Ex-Im Bank (The InterAmerican Dialogue, 2016; Bräutigam and Gallagher, 2014; Gallagher and Irwin, 2015). Delays and overruns of these projects have needed constant renegotiations of loan conditions, which require the debt to be serviced throughout the construction of the project and is not necessarily binding to the projects on-time completion. Policy makers are urged to run comprehensive risk assessments of possible unexpected events that could upset budgets and completion times of large-scale energy infrastructure.

- The conventional *ex-ante* energy system modelling for energy planning should be supplemented with an *ex-post* risk assessment, including the documented uncertainties of previous domestic or foreign energy projects – something that is rarely done today. For Ecuador, which by 2017 had already achieved a hydro-intensive electricity generation mix, and has five further hydropower projects in the pipeline (an additional 780 MW by 2020), it would be prudent to conduct an analysis of final cost and construction times once all eight flagship projects are commissioned, before embarking on further large hydropower capacity expansion efforts. According the Electricity Master Plan 2016-2025 MEER (2017a), the next 'strategic' hydropower project is Zamora-Santiago – a 3,600 MW reservoir hydropower station in the Santiago river (CELEC, 2017). This project already has final design studies and is expected to be built in three consecutive phases of 1,200 MW each by 2025. Policy makers are suggested to balance budgets and schedules of this mega-project under the light of the previous ones.

- It is suggested that Ecuador's energy planning authorities take into account the possible effects of climate change in terms of precipitation at the local level (both positive and negative occurrences). As our results have shown, there could be substantial reduction in the dry season from October to January which is coincident in both Pacific and Amazon regions and would lead to substantial reductions in hydropower production levels, regardless of the installed capacity. The untapped water resource potential in the Amazon region should be researched in greater detail in terms of climate change impacts and be complemented by social and financial feasibility studies of realistic investment options and requirements for hydropower development. The results of such studies should inform national low-emission development strategies that have a strong focus on hydropower and are presented as plans to comply with the country's Paris Agreement commitments. Hydropower could remain as a key mitigating technology but analyses should include a set of alternatives with non-hydro renewable energy sources, energy saving options and water use efficiencies, in order to avoid an over-reliance on a single technology and natural water resources. It is highlighted that only when detailed environmental assessments thereof yield results that are aligned with the findings of this study, can it justify pursuing a large expansion of the use of hydropower.

- The scenarios investigated in our study and the level of detail used in our computations suggest that possible future climatic trends will substantially impact hydropower production on a river basin level, with the uncertainty of magnitude and sign of change. Yet at the local level, individual hydropower plants may be subject to precipitation variability emanating from climate change that could lead to larger hydropower production losses than on average nation-wide. Since there are multiple uncertainties surrounding the long-term behaviour of precipitation patterns, as was shown from the disagreement among GCMs, it is recommended to continue multidisciplinary research such as the the hydrological + hydropower + energy system three-model-based approach presented in this thesis. Such research can yield insights that cannot be achieved from one disciplinary perspective, or through one type of model only.

- According to the results, constraining the deployment of new large hydropower projects in the Amazon region could lead to Ecuador introducing large shares of gas-fired thermoelectric generation with the consequential failure to meet climate change control contributions. Opening the Ecuadorian energy matrix to natural gas would need political will and significant investment, with the huge caveat of a power system lock-in to this energy source. Ecuador has small natural gas resources and therefore would need to rely on foreign imports of LNG, creating an energy security issue that leaves the country vulnerable to shortages and to the economic impacts due to the volatility of international energy markets. If the country fails to introduce natural gas into the matrix, the needed base load generation would need to be operated with liquid fuels, e.g. with heavy and residual fuel oil, as has currently been occurring in Ecuador. This would have devastating effects in terms of GHG emission and would leave the country with obsolete and low efficiency generation technologies. In this context, Ecuador should consider the deployment of non-hydro renewables as an insurance against a lock-in to gas, or ever worse a lock-in to liquid fossil fuels for power generation.

- Ecuador's government should be aware of some of the possible negative social, environmental and governance effects that accompany the deployment of large hydropower systems. At the local level, bottom-up social aspects and public acceptance related to the building of new hydropower dams may collide with top-down centralised plans pursued at the national level. In addition, the construction of large hydropower projects, necessitate significant financial and human capacity investments. Thus far, many contracts for hydropower construction have been granted without due competitive bidding, directly assigned to Chinese construction companies due to political alliances (Ray et al., 2015). This poses a challenge to future governance by hampering access to financing from international institutions for infrastructure endeavours in other economic sectors. In terms of capacity building, most of qualified workers have been coming from abroad without any local capacity building – large hydropower may help Ecuador to have electricity but not to develop other technical skills required for integral economic and social development. Among the environmental effects, the change of natural habitats for animals and vegetation may not be the only issues of large dams in sensible areas. The accumulation of waste products in the water reservoirs and associated emissions of environmental pollutants (including GHGs) could also offset the 'renewability' of hydropower energy. Ambitious hydropower development plans clearly necessitate independent environmental impact assessments.

Finally, large-scale electricity generation infrastructure projects are usually seen as strategic to increase energy security of supply at low costs. It is argued that the evidence shows that they should rather be seen as *'non-strategic'*. A paradigm shift from *'strategic projects'* to *'strategic portfolios'* is suggested. Energy planners should avoid focusing on a single or a few large one-of-a-kind projects, but instead assess alternatives of diversified investment portfolios that are economically viable, reduce risk and are able to meet the ultimate goal of supplying electricity demand within budget and on time.

Part V

APPENDIX AND BIBLIOGRAPHY

APPENDIX A

Table A.1: Inventory of new hydropower projects used to represent remaining hydropower potential in TIMES-EC

No.	Name	River	Capacity	Study level	Basin	Watershed
1	Santiago G8	Santiago	3,600	Final design	Santiago	Amazon
2	Santiago G9 y G10	Zamora	3,180	Prefeasibility	Santiago	Amazon
3	Verdeyacu Chico	Verdeyacu	1,172	Other estimated	Napo	Amazon
4	Catacahi	Mulatos	748	Other estimated	Napo	Amazon
5	Paute Cardenillo	Paute	596	Final design	Santiago	Amazon
6	Chespi -Palma real	Guayllabamba	460	Final design	Esmeraldas	Pacific
7	Cedroyacu	Chalupas	270	Other estimated	Napo	Amazon
8	El Retorno	Zamora	261	Other estimated	Santiago	Amazon
9	Tortugo	Guayllabamba	201	Feasibility	Esmeraldas	Pacific
10	Abitagua	Pastaza	198	Prefeasibility	Pastaza	Amazon
11	Lligua-Muyo	Pastaza, Muyo	170	Prefeasibility	Pastaza	Amazon
12	Llurimaguas	Guayllabamba	162	Feasibility	Esmeraldas	Pacific
13	Chirapi	Guayllabamba	160	Prefeasibility	Esmeraldas	Pacific
14	Calderón	Guayllabamba	147	Prefeasibility	Esmeraldas	Pacific
15	Parambas	Mira	145	Prefeasibility	Esmeraldas	Pacific
16	Los Bancos	Blanco	92.2	Other estimated	Esmeraldas	Pacific
17	Palanda 2	Palanda	84.7	Other estimated	Santiago	Amazon
18	San Pedro	Guayllabamba	83.4	Prefeasibility	Esmeraldas	Pacific
19	Las Cidras	Isimanchi	77.3	Other estimated	Santiago	Amazon
20	Lelia	Toachi	62.3	Other estimated	Esmeraldas	Pacific
21	Pilatón-Santa Ana	Pilaton	58.5	Other estimated	Esmeraldas	Pacific
22	Cubí	Guayllabamba	53	Prefeasibility	Esmeraldas	Pacific
23	Cuyes	Cuyes	51.3	Other estimated	Santiago	Amazon
24	Isimanchi	Isimanchi	51.1	Other estimated	Santiago	Amazon
25	Mira 2	Mira	47.8	Other estimated	Esmeraldas	Pacific
26	Cinto	Saloya/cinto	45.8	Other estimated	Esmeraldas	Pacific
27	Milpe	Blanco	43.7	Other estimated	Esmeraldas	Pacific
28	Vacas Galindo 2	Intag	42	Prefeasibility	Esmeraldas	Pacific
29	Mira	Mira	41	Other estimated	Esmeraldas	Pacific
30	Pamplonna	Intag	40.5	Other estimated	Esmeraldas	Pacific
31	La Barquillla	Chingual	40.1	Other estimated	Napo	Amazon
32	Guayabal	Mira	39.8	Other estimated	Esmeraldas	Pacific
33	Numbalá	Numbalá	39.2	Other estimated	Santiago	Amazon
34	Calderón II	San Pedro	38.7	Other estimated	Esmeraldas	Pacific

Table A.1 (continued)

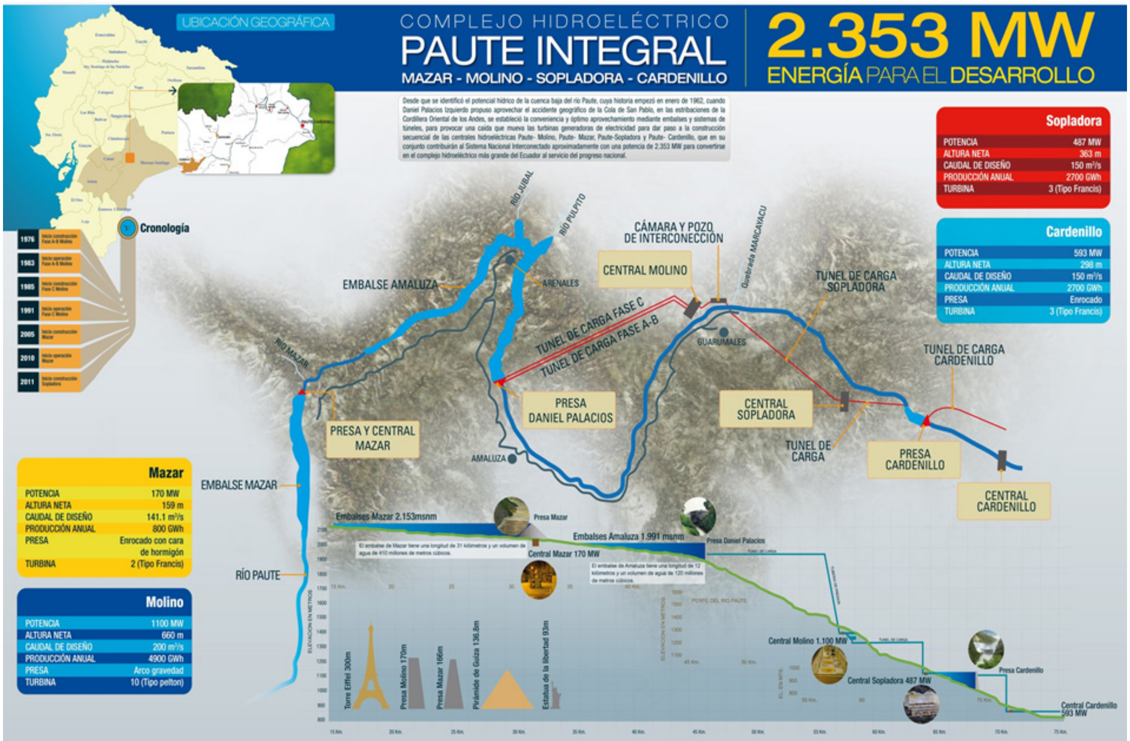
No.	Name	River	Capacity	Study level	Basin	Watershed
35	Negro (2)	Negro	36	Other estimated	Esmeraldas	Pacific
36	Puniyacu	Puniyacu	35.6	Other estimated	Esmeraldas	Pacific
37	Aluriquin	Toachi	34.5	Other estimated	Esmeraldas	Pacific
38	Yacuchaqui	Toachi	32.2	Other estimated	Esmeraldas	Pacific
39	Sucua	Tutanangoza	31.6	Other estimated	Santiago	Amazon
40	Gualleturo	Cañar	27.7	Other estimated	Jubones	Pacific
41	Las Juntas	Toachi	27.7	Other estimated	Esmeraldas	Pacific
42	Sarapullo	Sarapullo	27	Other estimated	Esmeraldas	Pacific
43	Cosanga	Cosanga	27	Other estimated	Napo	Amazon
44	Langoa	Langoa	26	Prefeasibility	Napo	Amazon
45	Paquishapa	Paquishapa	26	Other estimated	Jubones	Pacific
46	Chingual	Chigual	25.6	Other estimated	Napo	Amazon
47	Victoria 2	Pastaza	25	Prefeasibility	Pastaza	Amazon
48	Quijos-1	Quijos	24.2	Other estimated	Napo	Amazon
49	Chilma	Chilma	23.7	Other estimated	Esmeraldas	Pacific
50	El Cañaro	Yanuncay	5.6	Other estimated	Santiago	Amazon
51	Chinambi	Chinambi	5	Other estimated	Esmeraldas	Pacific
52	Tandayapa	Alambi	5	Other estimated	Esmeraldas	Pacific
53	Pacayacu 1	Quindigua	4.8	Other estimated	Guayas	Pacific
54	Huarhuallá	Huarhuallá	4.6	Other estimated	Pastaza	Amazon
55	Ambato	Ambato	4	Other estimated	Pastaza	Amazon
56	Chillayacu	Chillayacu	3.9	Other estimated	Jubones	Pacific
57	Chimbo-Guaranda	Illangama	3.8	Other estimated	Guayas	Pacific
58	Guápulo	Queb. El Batan	3.2	Prefeasibility	Esmeraldas	Pacific
59	La Concepcion	Santiaguillo	3.1	Other estimated	Esmeraldas	Pacific
60	Rircay	Rircay	3.1	Other estimated	Jubones	Pacific
61	Solanda	Solanda	3	Other estimated	Jubones	Pacific
62	El Laurel	La Plata	2.3	Other estimated	Esmeraldas	Pacific
63	Chuquiraguas	Chuquiraguas	2.3	Other estimated	Guayas	Pacific
64	Ganancay	Ganancay	2.2	Other estimated	Jubones	Pacific
65	Campo Bello	Suquibi	1.7	Other estimated	Guayas	Pacific
66	Intag 2	Intag	1.7	Final design	Esmeraldas	Pacific
67	Salunguire	Salunguire	1.7	Other estimated	Guayas	Pacific
68	Mariano Acosta	Chamachán	1.6	Other estimated	Esmeraldas	Pacific
69	Tululbi	Tululbi	1.6	Other estimated	Esmeraldas	Pacific
70	M.J. Calle	Canal de riego	1.4	Other estimated	Jubones	Pacific
71	Vacas Galindo 1	Intag	1.2	Other estimated	Esmeraldas	Pacific
72	Mirador 1	Gala	1.1	Prefeasibility	Jubones	Pacific
73	Rio Luis-2 (2)	Luis	1.1	Other estimated	Jubones	Pacific
	TOTAL		13,001.7			

Source: ARCONEL (2015)

Table A.2: Installed capacity and electricity generation per river basin in 2017

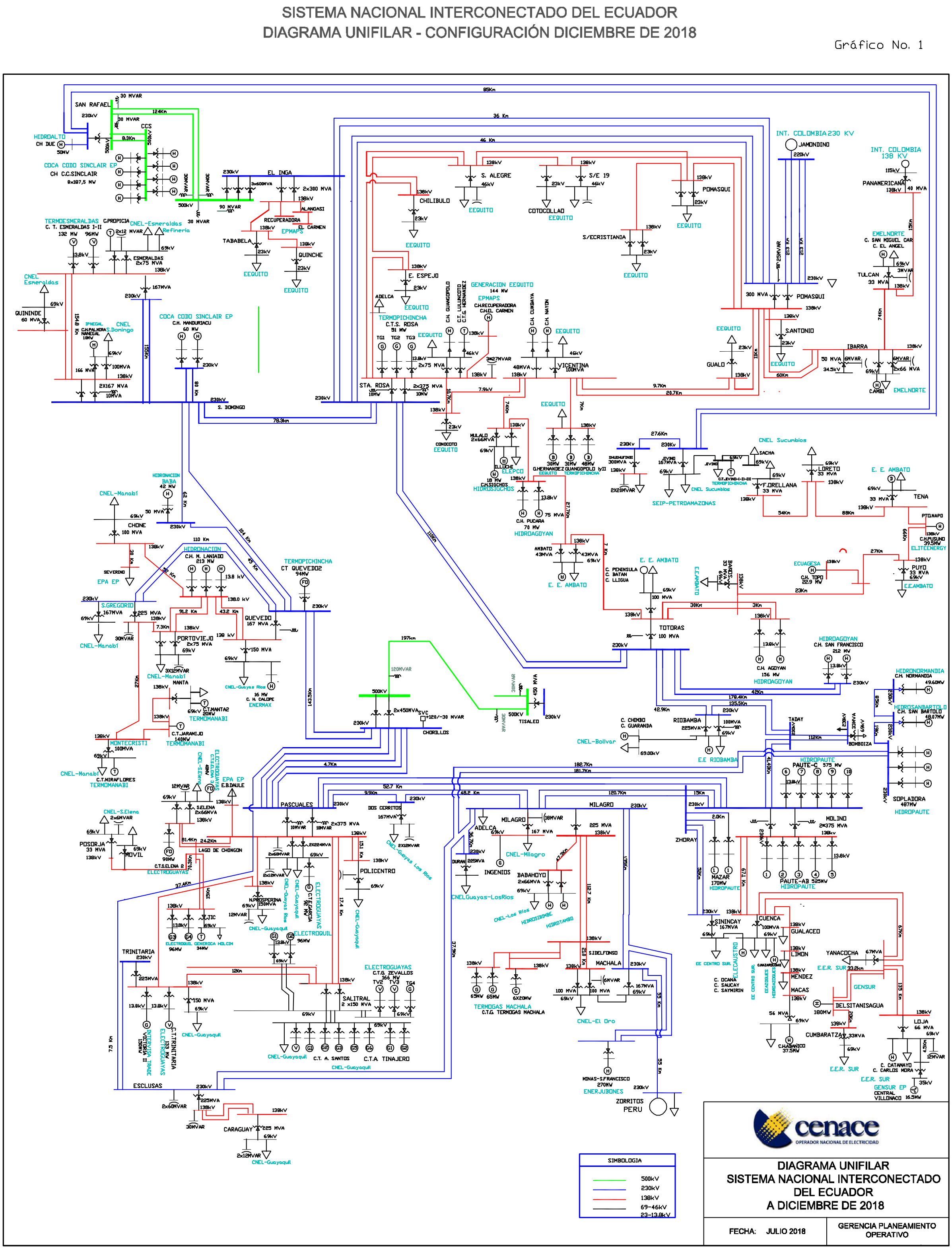
Watersheds	Basin	Installed capacity		Under construction	Remaining	Generation	
		MW	%	MW	MW	GWh	%
Pacific	Esmeraldas	240	5.5%	250	2,200	2,268	8.0%
	Guayas	290	6.6%	0	10	1,353	4.8%
	Jubones	20	0.5%	270	70	1,479	5.2%
Amazon	Santiago	1,850	42.0%	190	7,970	11,011	39.1%
	Pastaza	500	11.4%	0	500	2,888	10.2%
	Napo	1,500	34.1%	0.05	2,330	9,195	32.6%
Total		4,486	100%	710.05	13,080	28,194	1

Figure A.1: Paute Integral



Source: CELEC (2018a)

Figure A.2: Single line diagram of the Ecuadorian Interconnected System - SNI (2018)



Source: CENACE. Available at: www.cenace.org.ec

B

APPENDIX B

The allocation of the socio-economic drivers and the sensitivity parameters to model demand are shown in Table B.1. For example, the demand 'Food & beverage' will be projected as the associated driver gross domestic product (GDP) adjusted by the calibration parameters ranging from 1 to 0.65 from 2014 to 2050. The formula used in the automatic routine of TIMES is set as follows:

$$D_t = D_{t-1} * \left(Calibration + \left(\frac{Driver_t}{Driver_{t-1}} - 1 \right) * Sensitivity \right) \tag{B.1}$$

Figure B.1: Share of energy service demands according to industrial sub-sector

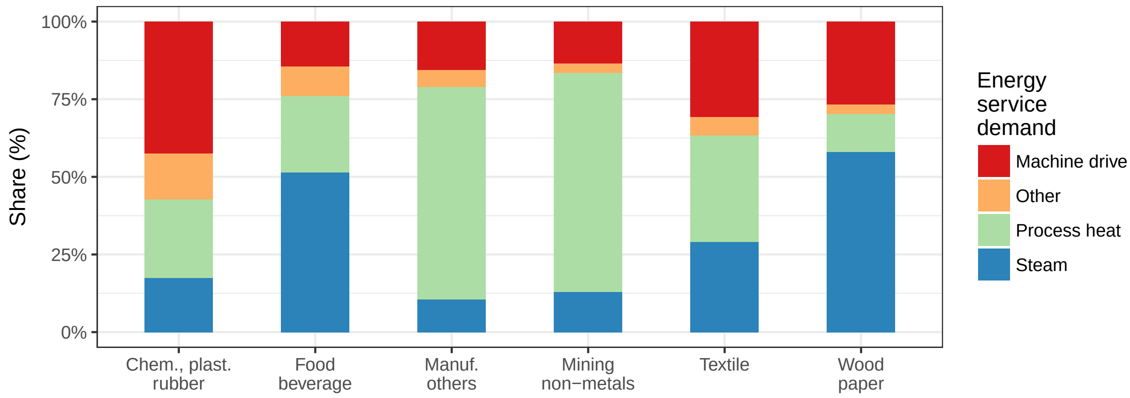


Table B.1: Socio-economic driver sensitivities

Sector	Sub-sector	Energy service demand	Driver	2014	2020	2030	2040	2050
Residential		Refrigeration	GDPHSH	1.0	0.95	0.86	0.78	0.70
		Lighting	GDPPC	1.0	0.95	0.86	0.78	0.70
		Water heating	GDPHSH	1.0	0.99	0.98	0.96	0.95
		Cooking	GDPHSH	1.0	0.96	0.89	0.82	0.75
		Other uses	GDPHSH	1.0	0.93	0.82	0.71	0.59
Industry	Food & beverage	Steam	GDP	1.0	0.94	0.84	0.74	0.65
	Minerals & non-metals	Machine drives	GDP	1.0	1.00	1.00	1.00	1.00
	Textile	Process heat	GDP	1.0	0.95	0.86	0.78	0.70
	Wood & paper	Other uses	GDP	1.0	0.93	0.82	0.71	0.59
	Chemicals, plastic & rubber		GDP	1.0	0.98	0.95	0.93	0.90
	Manufacturing & others		GDP	1.0	0.99	0.98	0.96	0.95
Commercial		Electrical appliances	GDPPC	1.0	0.97	0.93	0.89	0.85
		Other uses	GDPPC	1.0	0.92	0.80	0.67	0.54
Transport	Freight	Heavy freight	GDP	1.0	0.97	0.91	0.85	0.80
		Light freight	GDP	1.0	0.95	0.86	0.78	0.70
		Maritime	GDP	0.8	0.74	0.64	0.54	0.45
	Passengers	Private commute	GDPPC	1.2	1.11	0.95	0.80	0.64
		Public commute	GDPHSH	1.2	1.14	1.04	0.94	0.85
		Aviation	GDP	1.0	0.98	0.95	0.93	0.90
Agriculture, construction & others		Lighting	GDP	1.0	0.97	0.91	0.85	0.80
		Other uses	GDP	1.0	0.95	0.86	0.78	0.70

Table B.2: Transport sector vehicles fuel and efficiency assumptions, million vehicle-km/PJ

Technology	Class	Fuel	2015	2020	2030	2040	2050
Car	Alternative	Gas	38	38	38	38	38
	Conventional	Gasoline	35	35	36	37	45
	Alternative	Gas-hybrid	53	54	54	54	54
	Alternative	Gasoline-hybrid	36	37	38	39	40
	Alternative	Electric	30	30	30	30	30
	Alternative	LPG	35	35	35	35	35
Heavy freight	Conventional	Diesel	8	9	10	10	11
	Alternative	Diesel efficient 10%	10	11	12	12	13
	Alternative	Diesel efficient 20%	12	13	14	14	14
	Conventional	Gas	6	8	9	9	9
	Alternative	LPG	5	6	6	6	7
Light freight	Alternative	Gas	23	28	29	29	29
	Conventional	Diesel	20	20	21	22	23
	Alternative	Gas-hybrid	32	40	40	40	40
	Alternative	Diesel-hybrid	32	32	32	32	32
	Alternative	Electric	79	104	110	132	152
	Alternative	LPG	21	22	23	24	25
Bus	Conventional	Diesel	15	16	17	18	18
	Alternative	Diesel-hybrid	12	18	18	18	19
	Conventional	Gasoline	9	9	10	11	11

C

APPENDIX C

R script for creating GBM paths of correlated daily asset prices based on on Revell (2013) and Systematic-investor (2012).

Listing C.1: Function to create simulated asset paths in R

```
# GEOMETRIC BROWNIAN MOTION (GBM) - STOCHASTIC MODELLING OF ASSETS.
# SIMULATING MULTIPE ASSET PATHS IN R
# Based on: https://www.r-bloggers.com/simulating-multiple-asset-paths-in-r/

# INPUTS:

#s0 - stock price
# mu - expected return (growth rate)
# sigma - volatility
# nsteps - number of time steps to calculate
# dt - size of time steps
# nsims - number of simulation paths to generate

# OUTPUTS

# S - a matrix where each column represents a simulated asset price path.

# NOTES

# Calculate the drift:
#   nu = mu - sigma*sigma/2

# Generate potential paths
#   S = S0*[ones(1,nsims); cumprod(exp(nu*dt+sigma*sqrt(dt)*randn(steps,nsims)),1)]

################################################################################
```

```
# Load Systematic Investor Toolbox (SIT)
# <a class="vglnk" href="http://systematicinvestor.wordpress.com/systematic-
    investor-toolbox/" rel="nofollow"><span>http</span><span>://</span><span>
    systematicinvestor</span><span>.</span><span>wordpress</span><span>.</span><
    span>com</span><span>/</span><span>systematic</span><span>-</span><span>
    investor</span><span>-</span><span>toolbox</span><span>/</span></a>
###############################################################################

# Must install 'curl' package first and devtools
install.packages('curl', repos = 'http://cran.r-project.org')
devtools::install_github('systematicinvestor/SIT.date')

# Download Sistematic Investor Toolbox (SIT) database (http://systematicinvestor.
    github.io/about/)
curl_download('https://github.com/systematicinvestor/SIT/raw/master/SIT.tar.gz', '
    sit',mode = 'wb',quiet=T)
install.packages('sit', repos = NULL, type='source')

install.packages('truncnorm')
install.packages("gridGraphics")
install.packages("RCurl")
install.packages("ggpubr")

library(curl)
library('SIT')
library("reshape")
library("cowplot")
library("pryr")
library("gridGraphics")
library("xlsx")
library("ggplot2")
library("scales")
library("plotly")
library("dplyr")
library("ggthemes")
library("easyGgplot2")
library(devtools)
library(plyr)
library(gcookbook)
library(RCurl)
```

```
library(gridExtra)
library(cowplot)
library("ggpubr")

# Multiple paths function

asset.paths <- function(s0, mu, sigma,
                        nsims = 10000,
                        periods = c(0, 1)   # time periods at which to simulate
                            prices
)
{
  s0 = as.vector(s0)
  nsteps = len(periods)
  dt = c(periods[1], diff(periods))

  if( len(s0) == 1 ) {
    drift = mu - 0.5 * sigma^2
    if( nsteps == 1 ) {
      s0 * exp(drift * dt + sigma * sqrt(dt) * rnorm(nsims))
    } else {
      temp = matrix(exp(drift * dt + sigma * sqrt(dt) * rnorm(nsteps * nsims)), nc=
          nsims)
      for(i in 2:nsteps) temp[i,] = temp[i,] * temp[(i-1),]
      s0 * temp
    }
  } else {
    require(MASS)
    drift = mu - 0.5 * diag(sigma)
    n = len(mu)

    if( nsteps == 1 ) {
      s0 * exp(drift * dt + sqrt(dt) * t(mvrnorm(nsims, rep(0, n), sigma)))
    } else {
      temp = array(exp(as.vector(drift %*% t(dt)) + t(sqrt(dt) * mvrnorm(nsteps *
          nsims, rep(0, n), sigma))), c(n, nsteps, nsims))
      for(i in 2:nsteps) temp[,i,] = temp[,i,] * temp[,(i-1),]
      s0 * temp
    }
  }
```

```
}
```

Listing C.2: Code to visualize simulated asset paths in R

```
#*******************************************************************
# Plot some price paths
#*******************************************************************
S = c(48.94,4.5)
X = 98
Time = 0.5
r = 0.025
sigma = c(0.11,0.16)
rho = 0.74
N = 1000

# Single Asset for 33 years (2017-2050)
periods = 0:33

set.seed(100)

prices = asset.paths(S[1], r, sigma[1], N, periods = periods)

# plot
matplot(prices[,1:100], type='l', xlab='Years', ylab='Prices',
        main='Selected Price Paths')

# Multiple Assets for 33 years
periods = 0:33
cov.matrix = sigma%*%t(sigma) * matrix(c(1,rho,rho,1),2,2)
prices = asset.paths(S, c(r,r), cov.matrix, N, periods = periods)

# plot
layout(1:2)
matplot(prices[1,,1:100], type='l', xlab='Years', ylab='Prices',
        main='Selected Price Paths for Asset 1')
matplot(prices[2,,1:100], type='l', xlab='Years', ylab='Prices',
        main='Selected Price Paths for Asset 2')
```

Figure C.1: Simulated asset paths for only one asset

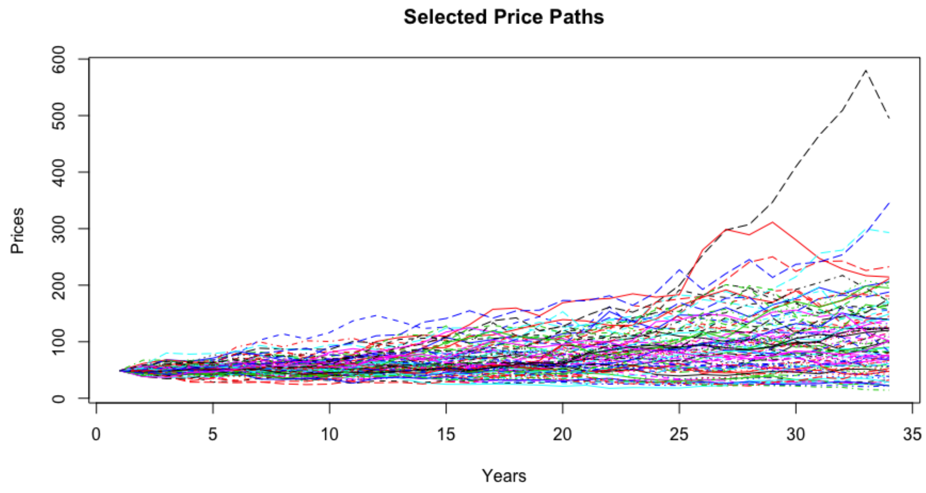


Figure C.2: Correlated simulated asset path for Asset 1

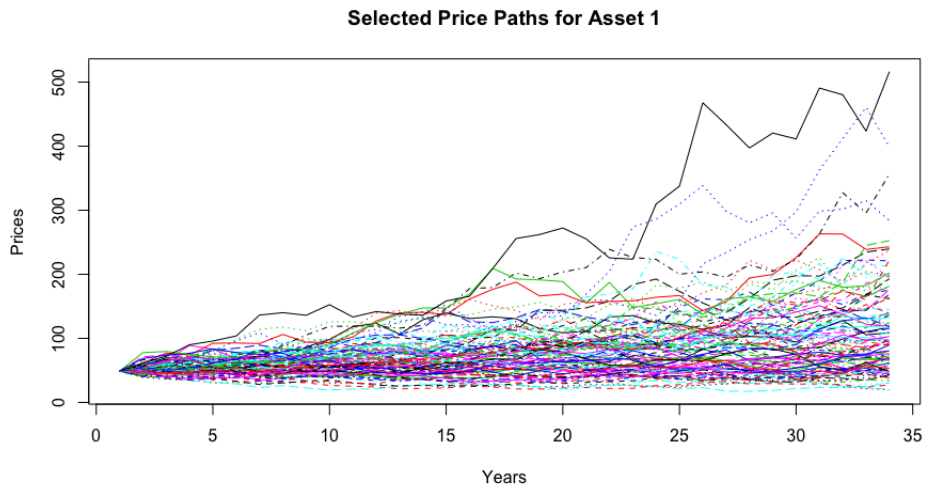
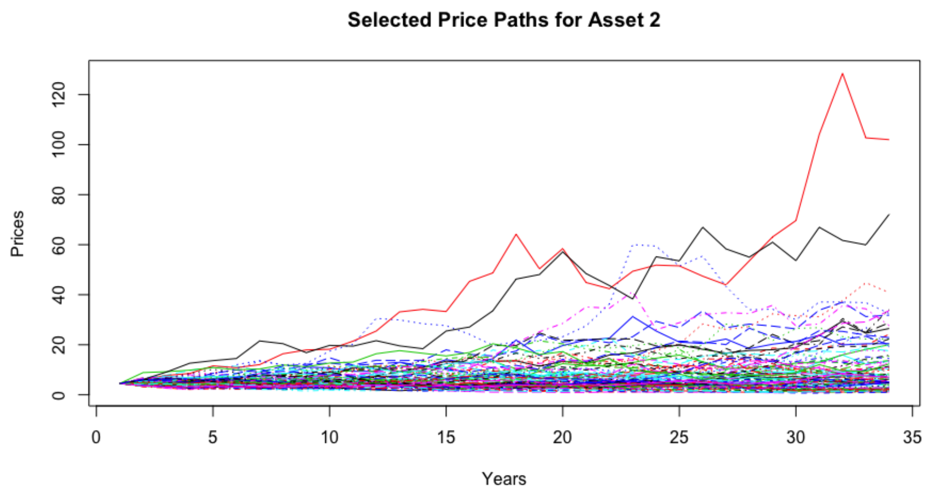


Figure C.3: Correlated simulated asset path for Asset 2



BIBLIOGRAPHY

Allan, G., Eromenko, I., McGregor, P., and Swales, K. (2011). The regional electricity generation mix in Scotland: A portfolio selection approach incorporating marine technologies. *Energy Policy*, 39(1):6–22. (Cited on pages 79, 82, 174, and 266.)

Alves (2013). Chinese Economic Statecraft: A Comparative Study of China's Oil-backed Loans in Angola and Brazil. *Journal of Current Chinese Affairs*, 42(1):99–130. (Cited on page 14.)

Amorim, F., Pina, A., Gerbelová, H., Pereira da Silva, P., Vasconcelos, J., and Martins, V. (2014). Electricity decarbonisation pathways for 2050 in Portugal: A TIMES (The Integrated MARKAL-EFOM System) based approach in closed versus open systems modelling. *Energy*, 69:104–112. (Cited on page 116.)

Anandarajah, G., Pye, S., Usher, W., Kesicki, F., and McGlade, C. E. (2011). TIAM-UCL Global Model Documentation Working Paper. (February). (Cited on pages 140 and 142.)

Anderson, E. P., Jenkins, C. N., Heilpern, S., Maldonado-ocampo, J. A., Carvajal-vallejos, F. M., Encalada, A. C., and Rivadeneira, J. F. (2018). Fragmentation of Andes-to-Amazon connectivity by hydropower dams. *Applied Ecology*, (January). (Cited on pages 4, 8, 9, 10, 15, 21, 92, 152, and 155.)

Ansar, A., Flyvbjerg, B., Budzier, A., and Lunn, D. (2014). Should we build more large dams? The actual costs of hydropower megaproject development. *Energy Policy*, 69:43–56. (Cited on pages 4, 14, 84, 85, and 154.)

ARCONEL (2015). Inventario de recursos energeticos del Ecuador con fines de produccion electrica - 2015. Technical report, Agencia de Regulacion y Control de Electricidad. (Cited on pages 10, 126, 151, 155, and 290.)

ARCONEL (2016). Estadística Anual y Multianual del Sector Eléctrico Ecuatoriano 2016. Technical report, Agencia de Regulacion y Control de Electricidad, Quito. (Cited on pages 114, 122, and 149.)

ARCONEL (2017). Balance Nacional de Energia Electrica a Octubre 2017. Technical report, Agencia de Regulacion y Control de Electricidad, Ecuador. (Cited on pages 113 and 114.)

ARCONEL (2018a). Balance Nacional Electrico Enero 2018. Technical report, Agencia de Regulacion y Control de Electricidad. (Cited on pages 114 and 136.)

ARCONEL (2018b). BalanceNacionalDiciembre2017. Technical report, Agencia de Regulacion y Control de Electricidad, Ecuador. (Cited on pages 113, 114, and 125.)

Arnell, N. W. (1992). Factors controlling the effects of climate change on river flow regimes in a humid temperate environment. *Journal of Hydrology*, 132(1-4):321–342. (Cited on pages 35 and 44.)

Arnell, N. W. (2010). Adapting to climate change: an evolving research programme. *Climatic Change*, 100(1):107–111. (Cited on page 62.)

Arnell, N. W., Vuuren, D. P. V., and Isaac, M. (2011). The implications of climate policy for the impacts of climate change on global water resources. *Global Environmental Change*, 21(2):592–603. (Cited on page 46.)

Arnesano, M., Carlucci, a. P., and Laforgia, D. (2012). Extension of portfolio theory application to energy planning problem - The Italian case. *Energy*, 39(1):112–124. (Cited on pages 79 and 83.)

Arnold, J. G., Srinivasan, R., Muttiah, R. S., and Williams, J. R. (1998). LARGE AREA HYDROLOGIC MODELING AND ASSESSMENT PART I: MODEL DEVELOPMENT. *Journal of the American Water Resources Association*, 34(1):73–89. (Cited on page 95.)

Arvizu, D., Balaya, P., Cabeza, L., Hollands, T., Jäger-Waldau, A., Kondo, M., Konseibo, C., Meleshko, V., Stein, W., Tamaura, Y., Xu, H., and Zilles, R. (2011). Direct Solar Energy. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Technical report. (Cited on page 28.)

Auffhammer, M. and Mansur, E. T. (2014). Measuring climatic impacts on energy consumption : A review of the empirical literature. *Energy Economics*, 46:522–530. (Cited on pages 32 and 34.)

Awerbuch, S. and Berger, M. (2003). Applying portfolio theory to EU electricity planning and policy-making. (Cited on pages 74, 77, 78, 79, 82, 159, and 160.)

Awerbuch, S., Stirling, A., Jansen, J. C., and Beurskens, L. W. M. (2006). Full-Spectrum Portfolio and Diversity Analysis of Energy Technologies. *Managing Enterprise Risk: What the Electric Industry Experience Implies for Contemporary Business*, pages 202–222. (Cited on page 80.)

Awerbuch, S. and Yang, S. (2007). Efficient electricity generating portfolios for Europe: Maximising energy security and climate change mitigation. *EIB Papers*, 12(2):8–37. (Cited on pages 5, 72, 78, 82, 108, 168, and 232.)

Awojobi, O. and Jenkins, G. P. (2015). Were the hydro dams financed by the World Bank from 1976 to 2005 worthwhile ? *Energy Policy*, 86:222–232. (Cited on page 85.)

Awojobi, O. and Jenkins, G. P. (2016). Managing the cost overrun risks of hydroelectric dams : An application of reference class forecasting techniques. *Renewable and Sustainable Energy Reviews*, 63:19–32. (Cited on pages 84 and 85.)

Babonneau, F., Haurie, A., Loulou, R., and Vielle, M. (2012). Combining Stochastic Optimization and Monte Carlo Simulation to Deal with Uncertainties in Climate Policy Assessment. *Environmental Modeling & Assessment*, 17(1):51–76. (Cited on page 76.)

Babur, M., Babel, M. S., Shrestha, S., Kawasaki, A., and Tripathi, N. K. (2016). Assessment of climate change impact on reservoir inflows using multi climate-models under RCPs-the case of Mangla Dam in Pakistan. *Water*, 8(9). (Cited on pages 15, 19, 93, and 105.)

Bacon, R. W. and Besant-Jones, J. E. (1998). Estimating construction costs and schedules. *Energy Policy*, 26(4):317–333. (Cited on page 4.)

Baede, M. (2010). IPCC Glossary AR4. Technical report. (Cited on page 39.)

Bakken, T. H., Modahl, I. S., Engeland, K., Raadal, H. L., and Arnøy, S. (2016). The life-cycle water footprint of two hydropower projects in Norway. *Journal of Cleaner Production*, 113:241–250. (Cited on pages 20 and 98.)

Baños, R., Manzano-Agugliaro, F., Montoya, F., Gil, C., Alcayde, A., and Gómez, J. (2011). Optimization methods applied to renewable and sustainable energy: A review. *Renewable and Sustainable Energy Reviews*, 15(4):1753–1766. (Cited on page 51.)

Bates, B., Kundzewicz, Z. W., Wu, S., and Palutikof, J. (2008). Climate Change and Water. Technical Paper of the Intergovernmental Panel on Climate Change. (Cited on pages 45, 70, 93, and 278.)

Bazmi, A. A. and Zahedi, G. (2011). Sustainable energy systems: Role of optimization modeling techniques in power generation and supply A review. *Renewable and Sustainable Energy Reviews*, 15(8):3480–3500. (Cited on page 51.)

BCE (2017). Previsiones Macroeconomicas 2017-2020. Technical report, Banco Central del Ecuador, Quito, Ecuador. (Cited on pages 122 and 138.)

Berga, L. (2016). The Role of Hydropower in Climate Change Mitigation and Adaptation : A Review. *Engineering*, 2(3):313–318. (Cited on pages 5, 7, and 19.)

Bertram, C., Johnson, N., Luderer, G., Riahi, K., Isaac, M., and Eom, J. (2015). Carbon lock-in through capital stock inertia associated with weak near-term climate policies. *Technological Forecasting and Social Change*, 90(Part A):62–72. (Cited on page 122.)

Bhattacharya, A. and Kojima, S. (2012). Power sector investment risk and renewable energy: A Japanese case study using portfolio risk optimization method. *Energy Policy*, 40:69–80. (Cited on page 82.)

Bhattacharyya, S. C. and Timilsina, G. R. (2010). A review of energy system models. *International Journal of Energy Sector Management*, 4(4):494–518. (Cited on pages 48, 49, and 116.)

Blackshear, B., Crocker, T., Drucker, E., and Filoon, J. (2011). Hydropower Vulnerability and Climate Change - A Framework for Modeling the Future of Global Hydroelectric Resources. In *Middlebury College Environmental Studies Senior Seminar*, page 82. (Cited on pages 4, 19, and 20.)

BNEF (2016). Global trends in clean energy investment. Technical Report April, Bloomberg New Energy Finance, London, United Kingdom. (Cited on pages 222 and 239.)

BNEF (2017). Electric Vehicle Outlook 2017. Technical Report July, Bloomberg New Energy Finance. (Cited on page 142.)

Bogmans, C. W. J., Dijkema, G. P. J., and Vliet, M. T. H. V. (2017). Adaptation of thermal power plants : The (ir) relevance of climate (change) information. *Energy Economics*, 62:1–18. (Cited on page 31.)

Börjeson, L., Höjer, M., Dreborg, K.-H., Ekvall, T., and Finnveden, G. (2006). Scenario types and techniques: Towards a user's guide. *Futures*, 38(7):723–739. (Cited on page 73.)

Bradfield, R., Wright, G., Burt, G., Cairns, G., and Van Der Heijden, K. (2005). The origins and evolution of scenario techniques in long range business planning. *Futures*, 37(8):795–812. (Cited on page 73.)

Bräutigam, D. and Gallagher, K. P. (2014). Bartering Globalization: China's Commodity-backed Finance in Africa and Latin America. *Global Policy*, 5(3):346–352. (Cited on page 283.)

Brealey, R. a., Myers, S. C., and Allen, F. (2011). *Principles of Corporate Finance*. (Cited on page 169.)

Buda, S., Huang, J., Zeng, X., Gao, C., and Jiang, T. (2017). Impacts of climate change on streamflow in the upper Yangtze River basin. *Climatic Change*, 141(3):533–546. (Cited on page 70.)

Burnett, D., Barbour, E., and Harrison, G. P. (2014). The UK solar energy resource and the impact of climate change. *Renewable Energy*, 71:333–343. (Cited on page 28.)

Buytaert, W. and Bièvre, B. D. (2012). Water for cities : The impact of climate change and demographic growth in the tropical Andes. 48(December 2011):1–13. (Cited on page 67.)

Buytaert, W., Célleri, R., and Timbe, L. (2009). Predicting climate change impacts on water resources in the tropical Andes: Effects of GCM uncertainty. *Geophysical Research Letters*, 36(7):1–5. (Cited on pages 8, 64, 183, and 252.)

Buytaert, W., Cuesta-Camacho, F., and Tobón, C. (2011). Potential impacts of climate change on the environmental services of humid tropical alpine regions. *Global Ecology and Biogeography*, 20(1):19–33. (Cited on pages 65, 99, and 279.)

Buytaert, W., Vuille, M., Dewulf, a., Urrutia, R., Karmalkar, a., and Célleri, R. (2010). Uncertainties in climate change projections and regional downscaling in the tropical Andes: Implications for water resources management. *Hydrology and Earth System Sciences*, 14(7):1247–1258. (Cited on pages 64, 72, 106, and 252.)

Cai, Y. and Arora, V. (2015). Disaggregating electricity generation technologies in CGE models: A revised technology bundle approach with an application to the U.S. Clean Power Plan. *Applied Energy*, 154:543–555. (Cited on page 49.)

Callaway, J. M. (2004). Adaptation benefits and costs: are they important in the global policy picture and how can we estimate them? *Global Environmental Change*, 14(3):273–282. (Cited on page 61.)

Callegari, C., Szklo, A., and Schaeffer, R. (2018). Cost overruns and delays in energy megaprojects : How big is big enough ? *Energy Policy*, 114(July 2017):211–220. (Cited on pages 4, 85, 152, and 265.)

Carter, T., Parry, M., Harasawa, H., and Nishioka, S. (1994). IPCC Technical Guidelines for Assessing Climate Change Impacts and Adaptations. Technical report, Intergovernmental Panel of Climate Change. (Cited on page 24.)

Carvajal, P. E., Li, F. G. N., Soria, R., Cronin, J., Anandarajah, G., and Mulugetta, Y. (2019). Large Hydropower, Decarbonisation and Climate Change Uncertainty: Modelling Power Sector Pathways for Ecuador. *Energy Stategy Reviews*, 23:86–99. (Cited on page 110.)

Castells-Quintana, D., Lopez-uribe, P., and Mcdermott, T. K. J. (2018). Adaptation to climate change : A review through a development economics lens. *World Development*, 104:183–196. (Cited on page 61.)

Cavalett, O., Chagas, M. F., Junqueira, T. L., Watanabe, M. D. B., and Bonomi, A. (2017). Environmental impacts of technology learning curve for cellulosic ethanol in Brazil. *Industrial Crops and Products*, 106:31–39. (Cited on page 259.)

CELEC (2013). Informe de rendición de cuentas 2013. Technical report, Corporacion Electrica del Ecuador. (Cited on page 113.)

CELEC (2017). Estudios Proyecto Zamora-Santiago. (Cited on pages 132, 153, 199, and 283.)

CELEC (2018a). Complejo Hidroeléctrico Paute Integral. (Cited on pages 115, 153, and 291.)

CELEC (2018b). Proyecto Sopladora. (Cited on page 10.)

Célleri, R. (2007). *Rainfall variability and rainfall-runoff dynamics in the Paute River Basin Southern Ecuadorian Andes*. PhD thesis, Katholieke Universiteit Leuven. (Cited on page 93.)

CENACE (2015). Informe Anual 2015. Technical Report 1, Operador Nacional de Electricidad, Quito - Ecuador. (Cited on pages 103, 104, and 144.)

CEPAL (2012). La economía del cambio climático en el Ecuador 2012. Technical report, Comision Economica para America Latina y el Caribe - Naciones Unidas, Santiago, Chile. (Cited on page 52.)

Chapman, L. (2007). Transport and climate change: a review. *Journal of Transport Geography*, 15(5):354–367. (Cited on page 34.)

Chavez-rodriguez, M. F., Carvajal, P. E., Martinez, J. E., Egüez, A., Esperanza, R., Mahecha, G., Schaeffer, R., Szklo, A., Lucena, A. F. P., and Arango, S. (2018). Fuel saving strategies in the Andes : Long-term impacts for Peru, Colombia and Ecuador. *Energy Strategy Reviews*, 20:35–48. (Cited on pages 147, 152, and 156.)

Chen, J., Brissette, F. P., Chaumont, D., and Braun, M. (2013). Performance and uncertainty evaluation of empirical downscaling methods in quantifying the climate change impacts on hydrology over two North American river basins. *Journal of Hydrology*, 479:200–214. (Cited on pages 41, 42, and 67.)

Chen, W., Yin, X., and Zhang, H. (2016). Towards low carbon development in China: a comparison of national and global models. *Climatic Change*, 136(1):95–108. (Cited on page 116.)

Chen, Z., Grasby, S. E., and Osadetz, K. G. (2004). Relation between climate variability and groundwater levels in the upper carbonate aquifer , southern Manitoba , Canada. *Journal of Hydrology*, 290:43–62. (Cited on page 45.)

Chiew, F. (2010). Estimation of rainfall elasticity of streamflow in Australia. *Hydrological Sciences Journal*. (Cited on page 37.)

Chiew, F. and McMahon, T. A. (2002). Global ENSO-streamflow teleconnection, streamflow forecasting and interannual variability. *Hydrological Sciences Journal*, 47(3):505–522. (Cited on page 45.)

Chiodi, A., Giannakidis, G., Labriet, M., Gallachóir, B. Ó., and Tosato, G. (2015). Introduction: Energy Systems Modelling for Decision Making. In *Informing Energy and Climate Policies Using Energy Systems Models*, chapter Introducti, pages 1–12. (Cited on pages 48 and 116.)

Ciscar, J.-C. and Dowling, P. (2014). Integrated assessment of climate impacts and adaptation in the energy sector. *Energy Economics*, 46:531–538. (Cited on page 63.)

Cisneros, J., B.E., T. O., Arnell, N., Benito, G., Cogley, J., Döll, P., Jiang, T., and Mwakalila, S. (2014). Freshwater resources. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical Report IPCC, IPCC. (Cited on pages 4, 18, 31, 35, 36, 42, 44, 46, 63, and 278.)

Collins, M., Knutti, R., Arblaster, J., Dufresne, J.-L., Fichefet, T., Friedlingstein, P., Gao, X., Gutowski, W. J., Johns, T., Krinner, G., Shongwe, M., Tebaldi, C., Weaver, A. J., and Wehner, M. (2013). Long-term Climate Change: Projections, Commitments and Irreversibility. *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, pages 1029–1136. (Cited on page 251.)

CONELEC (2008). Atlas Solar del Ecuador con fines de generacion electrica. Technical report, Consejo Nacional de Electricidad. (Cited on pages 134, 149, and 151.)

CONELEC (2013). Regulacion No. CONELEC - 001/13 "La participacion de los generadores de energia electrica producida con Recursos Energeticos Renovables No Convencionales". (Cited on page 113.)

Connolly, D., Lund, H., Mathiesen, B., and Leahy, M. (2010). A review of computer tools for analysing the integration of renewable energy into various energy systems. *Applied Energy*, 87(4):1059–1082. (Cited on pages 48 and 116.)

Cornelissen, T., Diekkrüger, B., and Giertz, S. (2013). A comparison of hydrological models for assessing the impact of land use and climate change on discharge in a tropical catchment. *Journal of Hydrology*, 498:221–236. (Cited on pages 43 and 70.)

Crespo, P., Feyen, J., Buytaert, W., Celleri, R., Frede, H., Ramirez, M., and Breuer, L. (2012). Development of a conceptual model of the hydrologic response of tropical Andean micro-catchments in Southern Ecuador. *Hydrology and Earth System Sciences Discussions*, pages 2475–2510. (Cited on page 183.)

Cronin, J., Anandarajah, G., and Dessens, O. (2018). Climate change impacts on the energy system: A review of trends and gaps. *Climatic Change*. (Cited on page 26.)

Cunado, J., Jo, S., and Perez de Gracia, F. (2015). Macroeconomic impacts of oil price shocks in Asian economies. *Energy Policy*, 86:867–879. (Cited on page 85.)

Cutforth, H. and Judiesch, D. (2007). Long-term changes to incoming solar energy on the Canadian Prairie. *Agricultural and Forest Meteorology*, 145(3-4):167–175. (Cited on page 28.)

da Cunha Saporta, L. A. (2017). *The role of hydro plants' reservoirs in wind power penetration in the Brazilian interconnected grid*. PhD thesis, Federal University of Rio de Janeiro. (Cited on page 256.)

Dale, L. L., Karali, N., Millstein, D., Carnall, M., Vicuña, S., Borchers, N., Bustos, E., O'Hagan, J., Purkey, D., Heaps, C., Sieber, J., Collins, W. D., and Sohn, M. D. (2015). An integrated assessment of water-energy and climate change in sacramento, california: how strong is the nexus? *Climatic Change*, pages 223–235. (Cited on pages 51, 52, 60, and 109.)

Daly, H. E. and Fais, B. (2014). UK TIMES MODEL. (November). (Cited on page 137.)

Damodaran (2008). Probabilisitc approaches: scenario analysis, decision trees and simulations. *Financial Times*, pages 1–61. (Cited on page 167.)

de França Doria, M., Boyd, E., Tompkins, E. L., and Adger, W. N. (2009). Using expert elicitation to define successful adaptation to climate change. *Environmental Science & Policy*, 12(7):810–819. (Cited on page 62.)

De-Llano Paz, F., Antelo, S. I., Calvo Silvosa, A., and Soares, I. (2014). The technological and environmental efficiency of the EU-27 power mix: An evaluation based on MPT. *Energy*, 69:67–81. (Cited on page 83.)

De Lucena, A., Schaeffer, R., and Szklo, A. (2010a). Least-cost adaptation options for global climate change impacts on the Brazilian electric power system. *Global Environmental Change*, 20(2):342–350. (Cited on pages 93 and 115.)

De Lucena, A. F., Szklo, A. S., Schaeffer, R., and Dutra, R. M. (2010b). The vulnerability of wind power to climate change in Brazil. *Renewable Energy*, 35(5):904–912. (Cited on pages 27 and 134.)

De Lucena, A. F. P., Szklo, A. S., Schaeffer, R., de Souza, R. R., Borba, B. S. M. C., da Costa, I. V. L., Júnior, A. O. P., and da Cunha, S. H. F. (2009). The vulnerability of renewable energy to climate change in Brazil. *Energy Policy*, 37(3):879–889. (Cited on pages 29, 51, 56, 59, 71, 93, and 251.)

Deane, J. P., Chiodi, A., Gargiulo, M., and Ó Gallachóir, B. P. (2012). Soft-linking of a power systems model to an energy systems model. *Energy*, 42(1):303–312. (Cited on pages 116 and 256.)

Debnath, K. B. and Mourshed, M. (2018). Challenges and gaps for energy planning models in the developing-world context. *Nature Energy*, 3(March). (Cited on page 34.)

Decarolis, J., Daly, H., Dodds, P., Keppo, I., Li, F., Mcdowall, W., Pye, S., Strachan, N., Trutnevyte, E., Usher, W., Winning, M., Yeh, S., and Zeyringer, M. (2017). Formalizing best practice for energy system optimization modelling. *Applied Energy*, 194:184–198. (Cited on pages 50, 72, 74, 75, 76, 122, and 159.)

Delang, C. O. and Toro, M. (2011). Hydropower-Induced Displacement and Resettlement in the Lao PDR. *South East Asia Research*, 19(3):567–594. (Cited on page 21.)

Delarue, E., De Jonghe, C., Belmans, R., and D'haeseleer, W. (2011). Applying portfolio theory to the electricity sector: Energy versus power. *Energy Economics*, 33(1):12–23. (Cited on pages 79, 80, and 82.)

Dell, J., Tierney, S., Franco, G., Newell, R. G., Richels, R., Weyant, J., and Wilbanks, T. J. (2014). Ch. 4: Energy Supply and Use. Climate Change Impacts in the United States: The Third National Climate Assessment, J. M. Melillo, Terese (T.C.) Richmond, and G. W. Yohe, Eds. Technical report, USGCRP (U.S. Global Climate Research Program). (Cited on page 32.)

Devkota, L. P. and Gyawali, D. R. (2015). Impacts of climate change on hydrological regime and water resources management of the Koshi River Basin , Nepal. *Journal of Hydrology : Regional Studies*, 4:502–515. (Cited on page 43.)

Diaz, E. M., Molero, J. C., and Perez de Gracia, F. (2016). Oil price volatility and stock returns in the G7 economies. *Energy Economics*, 54:417–430. (Cited on page 85.)

Dodds, P. E. (2010). *Development of a crop model to examine crop management and climate change in Senegal*. PhD thesis, University of Leeds. (Cited on page 44.)

DOE (2013). US Energy Sector Vulnerabilities to Climate Change and Extreme Weather. Technical Report August, US DEPARTMENT OF ENERGY. (Cited on pages 31 and 32.)

DOE (2015). Climate Change and the U.S. Energy Sector: Regional Vulnerabilities and Resilience Solutions. Technical report, US Department of Energy. (Cited on pages 4, 24, 25, 30, 31, 32, 61, 62, and 259.)

Douglass, M. (2016). *Cross-border water governance in Asia*. Number October 2013. United Nations University. (Cited on page 21.)

Ebinger, J. and Vergara, W. (2011). *Climate Impacts on Energy Systems*. (Cited on pages 28, 30, and 33.)

ECLAC (2017). Economic Survey of Latin America and the Caribbean 2017. Technical report, Economic Comision for Latin America and the Caribbean, Santiago, Chile. (Cited on page 111.)

Edenhofer, O. (2011). The IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation. Number September. (Cited on pages 18 and 28.)

Egre, D. and Milewski, J. C. (2002). The diversity of hydropower projects. *Energy Policy*, 30:1225–1230. (Cited on page 12.)

EIA (2017). Annual Energy Outlook 2017. Technical report, U.S. Energy Information Administration. (Cited on pages 85, 148, 150, 172, 173, and 209.)

EIA (2018a). Annual Energy Outlook (AEO) Retrospective Review : Evaluation of AEO2018 and Previous Reference Case Projections. Technical Report December, US Energy Information Administration. (Cited on page 148.)

EIA (2018b). Electric Power Monthly - U.S. Energy Information Administration. Technical report. (Cited on page 30.)

Eisner, S., Flörke, M., Chamorro, A., Daggupati, P., Donnelly, C., Huang, J., Hundecha, Y., Koch, H., Kalugin, A., Krylenko, I., Mishra, V., Piniewski, M., Samaniego, L., Seidou, O., Wallner, M., and Krysanova, V. (2017). An ensemble analysis of climate change impacts on streamflow seasonality across 11 large river basins. *Climatic Change*, 141(3):401–417. (Cited on page 70.)

El Comercio (2016). Cuatro turbinas del Coca-Codo comenzaron a entregar energía en firme | El Comercio. (Cited on page 11.)

Endo, E. (2007). Market penetration analysis of fuel cell vehicles in Japan by using the energy system model MARKAL. *International Journal of Hydrogen Energy*, 32(10-11):1347–1354. (Cited on page 116.)

Escobar, M., López, F. F., and Clark, V. (2011). Energy-Water-Climate Planning for Development Without Carbon in Latin America and the Caribbean. Technical Report November, Stockholm Environment Institute-U.S. Center. (Cited on pages 59, 71, 185, and 278.)

Escribano, G. (2013). Ecuador's energy policy mix: Development versus conservation and nationalism with Chinese loans. *Energy Policy*, 57:152–159. (Cited on page 154.)

Espinoza Villar, J. C., Ronchail, J., Guyot, J. L., Cochonneau, G., Naziano, F., Lavado, W., De Oliveira, E., Pombosa, R., and Vauchel, P. (2009). Spatio-temporal rainfall variability in the Amazon basin countries (Brazil, Peru, Bolivia, Colombia, and Ecuador). *International Journal of Climatology*, 29(11):1574–1594. (Cited on page 99.)

Eurostat (2013). Electricity production and supply statistics. Technical report. (Cited on page 30.)

Fabozzi, F. J., Gupta, F., and Markowitz, H. M. (2009). The Legacy of Modern Portfolio Theory. (Cited on page 77.)

Fais, B. and Blesl, M. (2015). Integrating Policy Instruments into Energy System Models - From Theory to Application to Germany. In *Informing Energy and Climate Policies Using Energy Systems Models*, pages 125–139. (Cited on page 116.)

Fais, B., Keppo, I., Zeyringer, M., Usher, W., and Daly, H. (2016). Impact of technology uncertainty on future low-carbon pathways in the UK. *Energy Strategy Reviews*, 13-14:154–168. (Cited on page 75.)

Fang, G. H., Yang, J., Chen, Y. N., and Zammit, C. (2015). Comparing bias correction methods in downscaling meteorological variables for a hydrologic impact study in an arid area in China. *Hydrology and Earth System Sciences*, 19(6):2547–2559. (Cited on page 105.)

Fant, C., Adam Schlosser, C., and Strzepek, K. (2016). The impact of climate change on wind and solar resources in southern Africa. *Applied Energy*, 161:556–564. (Cited on page 28.)

Fearnside, P. M. (2015). Amazon dams and waterways: Brazil's Tapajós Basin plans. *Ambio*, 44(5):426–439. (Cited on page 154.)

Feretic, D. and Tomsic, Z. (2005). Probabilistic analysis of electrical energy costs comparing: production costs for gas, coal and nuclear power plants. *Energy Policy*, 33(1):5–13. (Cited on page 168.)

Ferreira, P. and Cunha, J. (2012). On the use of MPT to Derive Optimal RES Electricity Generation Mixes. In *2012 25th Internation Conference on Efficiency, Cost, Optimization, Simulation and Environmental Impact of Energy Systems*, pages 1–15, Perugia, Italy. (Cited on pages 79 and 82.)

Fichter, T., Soria, R., Szklo, A., Schaeffer, R., and Lucena, A. F. P. (2017). Assessing the potential role of concentrated solar power (CSP) for the northeast power system of Brazil using a detailed power system model. *Energy*, 121:695–715. (Cited on pages 134, 137, and 256.)

Finer, M. and Jenkins, C. N. (2012a). Proliferation of Hydroelectric Dams in the Andean Amazon and Implications for Andes-Amazon Connectivity. *PLoS ONE*, 7(4):e35126. (Cited on page 8.)

Finer, M. and Jenkins, C. N. (2012b). Proliferation of Hydroelectric Dams in the Andean Amazon and Implications for Andes-Amazon Connectivity. *PLoS ONE*, 7(4):e35126. (Cited on pages 92 and 279.)

Flowers, M. E., Smith, M. K., Parsekian, A. W., Boyuk, D. S., McGrath, J. K., and Yates, L. (2016). Climate impacts on the cost of solar energy. *Energy Policy*, 94:264–273. (Cited on page 28.)

Flyvbjerg, B. (2014). From Academia : Summaries of New Research for the Reflective Practitioner What You Should Know about Megaprojects and Why: An Overview. Technical report, Project Management Institute. (Cited on page 84.)

Fortes, P., Alvarenga, A., Seixas, J., and Rodrigues, S. (2014a). Long-term energy scenarios: Bridging the gap between socio-economic storylines and energy modeling. *Technological Forecasting and Social Change*, 91:161–178. (Cited on page 73.)

Fortes, P., Pereira, R., Pereira, A., and Seixas, J. (2014b). Integrated technological-economic modeling platform for energy and climate policy analysis. *Energy*, 73:716–730. (Cited on page 50.)

Forzieri, G., Bianchi, A., Silva, F. B. e., Marin Herrera, M. A., Leblois, A., Lavalle, C., Aerts, J. C. J. H., and Feyen, L. (2018). Escalating impacts of climate extremes on critical infrastructures in Europe. *Global Environmental Change*, 48:97–107. (Cited on page 32.)

Fowler, H. J., Blenkinsop, S., and Tebaldi, C. (2007). Linking climate change modelling to impacts studies: recent advances in downscaling techniques for hydrological modelling. *International Journal of Climatology*, 27(12):1547–1578. (Cited on pages 41 and 105.)

Gaetani, M., Huld, T., Vignati, E., Monforti-Ferrario, F., Dosio, A., and Raes, F. (2014). The near future availability of photovoltaic energy in Europe and Africa in climate-aerosol modeling experiments. *Renewable and Sustainable Energy Reviews*, 38:706–716. (Cited on page 28.)

Gallagher, K. and Irwin, A. (2015). China's economic statecraft in Latin America: Evidence from China's policy banks. *Pacific Affairs*, 88(1):99–121. (Cited on page 283.)

Gargiulo, M. (2009). Getting Started with TIMES-VEDA. Technical Report May, ETSAP. (Cited on page 98.)

Gargiulo, M. and Gallachóir, B. Ó. (2013). Long-term energy models: Principles, characteristics, focus, and limitations. *Wiley Interdisciplinary Reviews: Energy and Environment*, 2(2):158–177. (Cited on page 115.)

Gaudard, L. (2015). Pumped-storage project: A short to long term investment analysis including climate change. *Renewable and Sustainable Energy Reviews*, 49:91–99. (Cited on page 54.)

Gaudard, L., Gilli, M., and Romerio, F. (2013). Climate Change Impacts on Hydropower Management. *Water Resources Management*, 27(15):5143–5156. (Cited on pages 19 and 48.)

GCI (2016). THE GLOBAL STATUS OF CCS | 2016. Technical report, Global CCS Institute. (Cited on pages 136 and 137.)

GEA (2012). Global Energy Assessment: Toward a Sustainable Future. page 1865. (Cited on page 5.)

Gernaat, D. E. H. J., Bogaart, P. W., Vuuren, D. P. V., Biemans, H., and Niessink, R. (2017). High-resolution assessment of global technical and economic hydropower potential. *Nature Energy*, 2(October). (Cited on pages 7, 8, 19, 53, 60, and 128.)

Gnann, T., Stephens, T. S., Lin, Z., Plötz, P., Liu, C., and Brokate, J. (2018). What drives the market for plug-in electric vehicles? - A review of international PEV market diffusion models. *Renewable and Sustainable Energy Reviews*, 93:158–164. (Cited on page 140.)

Goddard (2015). Option Pricing - Generating Correlated Random Sequences. (Cited on page 171.)

Golombek, R., Kittelsen, S. A. C., and Haddeland, I. (2012). Climate change: impacts on electricity markets in Western Europe. *Climatic change*, 113(2):357–370. (Cited on pages 5, 59, and 71.)

González-Zeas, D., Chávez-Jiménez, A., Coello-Rubio, X., and Correa, Á. (2014). Pluviometric characterization of the Coca river basin by using a stochastic rainfall model. *Geophysical Research Abstracts Vol. 16*, 16:8620. (Cited on page 183.)

Gosling, S. N., Taylor, R. G., Arnell, N. W., and Todd, M. C. (2011). A comparative analysis of projected impacts of climate change on river runoff from global and catchment-scale hydrological models. *Hydrology and Earth System Sciences*, 15(1):279–294. (Cited on pages 35 and 188.)

Gracey, E. O. and Verones, F. (2016). Impacts from hydropower production on biodiversity in an LCA framework—review and recommendations. *The International Journal of Life Cycle Assessment*, 21(3):412–428. (Cited on pages 21 and 154.)

Graham, L. P., Hagemann, S., Jaun, S., and Beniston, M. (2007). On interpreting hydrological change from regional climate models. *Climatic Change*, 81(S1):97–122. (Cited on page 70.)

GRDC (2016). The Global Runoff Data Centre. Technical report, 56068 Koblenz, Germany. (Cited on pages 101 and 252.)

Green, T. R., Taniguchi, M., Kooi, H., Gurdak, J. J., Allen, D. M., Hiscock, K. M., Treidel, H., and Aureli, A. (2011). Beneath the surface of global change : Impacts of climate change on groundwater. *Journal of Hydrology*, 405(3-4):532–560. (Cited on pages 37, 41, 42, and 45.)

Gregg, R. M., Kershner, J. M., Hansen, L. J., and Island, B. (2018). *Strategies for Climate Change Adaptation : A Synthesis*. Elsevier Inc. (Cited on pages 61 and 62.)

Grijsen, J. (2014). Understanding the Impact of Climate Change on Hydropower: the case of Cameroon. Technical Report Repoirt No. 87913, The World Bank - Africa Energy Practice. (Cited on pages 19, 52, 60, 71, and 93.)

Gritsevskyi, A. and Nakićenovi, N. (2000). Modeling uncertainty of induced technological change. *Energy Policy*, 28(13):907–921. (Cited on page 167.)

Grubler, A. and Fuss, S. (2012). Technology Portfolios: Modeling Technological Uncertainty and Innovation Risks. Historical Case Studies of Energy Technology Innovation in: Chapter 24, The Global Energy Assessment. *Historical Case Studies of Energy Technology Innovation in: Chapter 24, The Global Energy Assessment*, pages 1–12. (Cited on pages 79 and 82.)

Grumbine, R. E., Dore, J., and Xu, J. (2012). Mekong hydropower: drivers of change and governance challenges. *Frontiers in Ecology and the Environment*, 10(2):91–98. (Cited on page 21.)

Guilhoto, J. J. M., Sesso Filho, U. a. (2005). Estimação da Matriz Insumo-Produto a Partir de Dados Preliminares das Contas Nacionais. *Economia Aplicada*, 9(2):277–299. (Cited on page 48.)

Hadian, S. and Madani, K. (2014). A New Finance-based Portfolio Analysis Framework for Sustainable Energy Planning. In *World Environmental and Water Resources Congress 2014: Water without Borders*, pages 2043–2053. (Cited on pages 78, 83, and 266.)

Hallegatte, S., Przyluski, V., and Vogt-schilb, A. (2011). Building world narratives for climate change impact, adaptation and vulnerability analyses. *Nature Climate Change*, 1(3):151–155. (Cited on page 61.)

Hamlet, A. F., Lee, S.-Y., Mickelson, K. E. B., and Elsner, M. M. (2010). Effects of projected climate change on energy supply and demand in the Pacific Northwest and Washington State. *Climate change*, 102(1-2):103–128. (Cited on pages 47, 51, 59, and 72.)

Harou, J. J., Azuara, J. M., Zhu, T., Tanaka, S. K., Lund, J. R., Stine, S., Olivares, M. A., and Jenkins, M. W. (2010). Economic consequences of optimized water management for a prolonged , severe drought in California. *Water Resources Research*, 46. (Cited on page 14.)

Harris, I., Jones, P. D., Osborn, T. J., and Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. *International Journal of Climatology*, 34(3):623–642. (Cited on pages 101 and 252.)

Harrison, G. P. and Whittington, H. W. (2002). Susceptibility of the Batoka Gorge hydroelectric scheme to climate change. *Journal of Hydrology*, 264(1-4):230–241. (Cited on pages 51, 57, 59, and 251.)

Harsem, Ø., Eide, A., and Heen, K. (2011). Factors influencing future oil and gas prospects in the Arctic. *Energy Policy*, 39(12):8037–8045. (Cited on page 31.)

Harto, C. and Yan, Y. (2011). Analysis of drought impacts on electricity production in the western and texas interconnections of the United States. Technical report, Argonne National Laboratory, Chicago. (Cited on page 14.)

Hatfield, J., Takle, G., Grotjahn, R., Holden, P., Izaurralde, R. C., Mader, T., Marshall, E., and Liverman, D. (2014). Ch. 6: Agriculture. Climate Change Impacts in the United States: The Third National Climate Assessment. Technical report. (Cited on page 34.)

Hattermann, F., Vetter, T., Breuer, L., Su, B., Daggupati, P., Donnelly, C., Fekete, B., Florke, F., Gosling, S., Hoffmann, P., Liersch, S., Masaki, Y., Motovilov, Y., Muller, C., Samaniego, L., Stacke, T., Wada, Y., Yang, T., and Krysnaova, V. (2018). Sources of uncertainty in hydrological climate impact assessment : a cross-scale study. *Environmental Research Letters*, 13(015006). (Cited on page 70.)

Hay, L. E., Clark, M. P., Wilby, R. L., Gutowski, W. J., Leavesley, G. H., Pan, Z., Arritt, R. W., and Takle, E. S. (2002). Use of Regional Climate Model Output for Hydrologic Simulations. *Journal of Hydrometeorology*, 3(5):571–590. (Cited on page 35.)

Hdidouan, D. and Staffell, I. (2017). The impact of climate change on the levelised cost of wind energy. *Renewable Energy*, 101:575–592. (Cited on page 27.)

Herbst, A., Eberhard, J., Reitze, F., and Felipe (2012a). Bridging macroeconomic and bottom up energy models: The case of efficiency in industry. Technical report, ECEEE 2012 SUMMER STUDY on Ener gy efficiency in industry. (Cited on pages 48 and 49.)

Herbst, A., Toro, F., Reitze, F., and Jochem, E. (2012b). Introduction to energy systems modelling. *Swiss J. Econ. Stat*, 148(2):111–135. (Cited on pages 48, 49, and 50.)

Herzog, S., Martínez, R., Jørgensen, P., and Tiessen, H. (2011). Climate change and biodiversity in the tropical Andes. Technical report, Inter-American Institute for Global Change Research (IAI) and Scientific Committee on Problems of the Environment (SCOPE). (Cited on page 8.)

Heuberger, C. F. and Dowell, N. M. (2018). Real-World Challenges with a Rapid Transition to 100 % Renewable Power Systems. *Joule*, 2(3):367–370. (Cited on page 174.)

Hirsch, R. (2003). *Technology and Transformation in the American Electric Utility Industry*. Cambridge University Press. (Cited on page 224.)

Ho, J. T., Thompson, J. R., and Brierley, C. (2015). Projections of hydrology in the Tocantins-Araguaia Basin, Brazil: uncertainty assessment using the CMIP5 ensemble. *Hydrological Sciences Journal*, 6667(July):150603015228007. (Cited on pages 42, 96, 108, 109, 184, 185, 253, and 278.)

Holttinen, H., Kiviluoma, J., Forcione, A., Milligan, M., Smith, C., Dillon, J., O'Malley, M., Dobschinski, J., van Roon, S., Cutululis, N., Orths, A., Borre, P., Carlini, M., Estanqueiro, A., Bessa, R., Soder, L., Farahmand, H., Rueda, J., Jianhua, B., Kondoh, J., Pineda, I., and Strbac, G. (2016). Design and operation of power systems with large amounts of wind power (Final summary report). Technical report, IEA Wind Task 25. VTT. (Cited on page 134.)

Hourcade, J.-C., Jaccard, M., Bataille, C., and Ghersi, F. (2006). Hybrid Modeling: New Answers to Old Challenges Introduction to the Special Issue of The Energy Journal. (Cited on page 49.)

Hu, M.-C. and Hobbs, B. F. (2010). Analysis of multi-pollutant policies for the U.S. power sector under technology and policy uncertainty using MARKAL. *Energy*, 35(12):5430–5442. (Cited on page 75.)

Hu, Y., Maskey, S., and Uhlenbrook, S. (2013). Downscaling daily precipitation over the Yellow River source region in China: a comparison of three statistical downscaling methods. *Theoretical and Applied Climatology*, 112(3):447–460. (Cited on page 105.)

Hua, W., Chen, H., and Zhou, L. (2015). Assessing climatic impacts of future land use and land cover change projected with the CanESM2 model. 3675(December 2014):3661–3675. (Cited on page 44.)

Hull, J. C. (2003). *Options futures and other derivatives*. Pearson Education India. (Cited on page 169.)

IADB (2017). La red del futuro. Technical report, Inter American Development Bank, Washington D.C. U.S.A. (Cited on page 8.)

IEA (2011). World Energy Model - Modelling the capacity credit of renewable energy sources. Technical report, International Energy Agency. (Cited on page 134.)

IEA (2014a). Energy Technology Perspectives 2014 Executive Summary. page 14. (Cited on page 5.)

IEA (2014b). IEA STATISTICS - OIL INFORMATION. Technical report, International Energy Agency, Paris. (Cited on page 85.)

IEA (2014c). Technology Roadmap Solar photovoltaic energy. Technical report, International Energy Agency, Paris. (Cited on pages 134 and 137.)

IEA (2015). Projected Costs of Generating Electricity. Technical report, International Energy Agency, Paris. (Cited on page 134.)

IEA (2016a). Global EV Outlook 2016 Beyond one million electric cars. Technical report, International Energy Agency. (Cited on page 142.)

IEA (2016b). Key World Energy Statistics. Technical report, International Energy Agency, Paris. (Cited on pages 3, 8, 122, 136, and 137.)

IEA (2016c). The potential for equipping China's existing coal fleet with carbon capture and storage. Technical report, International Energy Agency. (Cited on page 136.)

IEA (2017). Gas 2O17 - Market Report Series. Technical report, International Energy Agency, Paris. (Cited on page 263.)

IEA (2018). The Future of Cooling - Opportunities for energy-efficient air conditioning. Technical report, International Energy Agency, Paris. (Cited on pages 33 and 261.)

IGU (2017). 2017 World LNG Report. Technical report, International Gas Union. (Cited on page 148.)

IHA (2017). Hydropower Status Report 2017. Technical report, International Hydropower Association. (Cited on page 10.)

IHA (2018). Hydropower status report 2018. Technical report, International Hydropower Association. (Cited on pages 3, 6, 7, 8, 12, and 18.)

Iimi, A. (2007). Estimating Global Climate Change Impacts on Hydropower Projects : Applications in India, Sri Lanka and Vietnam. (Cited on pages 52 and 59.)

INEC (2017). Estadisticas Nacionales. (Cited on pages 138 and 253.)

INER (2015). Servicio de Capacitatcion en Modelamiento de Escenarios Prospectivos para el Personal del Poryecto "Evaluacion e implementacion de metodologias de elaboracion de balance y prospectiva energetica y sostenibilidad nacionalâ. Technical report, Instituto Nacional de Eficienca Energetica y Energia Renovable, Ecuador. (Cited on page 142.)

IPCC (2007). *Climate Change 2007 - Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Fourth Assessment Report of the IPCC*. Cambridge University Press. (Cited on pages 23, 37, and 44.)

IPCC (2011). IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation: Hydropower. Technical report, IPCC. (Cited on pages 19 and 20.)

IPCC (2012). Renewable Energy Sources and Climate Change Mitigation. Technical report, Intergovernmental Panel on Climate Change. (Cited on pages 13 and 45.)

IPCC (2013). Summary for Policymakers. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Technical report, IPCC. (Cited on pages 109 and 185.)

IPCC (2014a). Climate Change 2014: Impacts, Adaptation and Vulnerability - Contributions of the Working Group II to the Fifth Assessment Report - Summary for Policy Makers. Technical report, INTERGOVERNMENTAL PANEL ON CLIMATE CHANGE. (Cited on pages 23 and 278.)

IPCC (2014b). Climate Change 2014 Synthesis Report Summary Chapter for Policymakers. Technical report. (Cited on page 66.)

IPCC (2014c). Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, Intergovernmental Panel on Climate Change. (Cited on page 63.)

IPCC (2014d). Technical Summary - IPCC 5th Assessment Report "Climate Change 2014: Mitigation of Climate Change". Technical report. (Cited on pages 3 and 23.)

IRENA (2012a). Biomass for Power Generation. Technical Report June, International Renewable Energy Agency. (Cited on pages 137 and 258.)

IRENA (2012b). Hydropower. Technical Report 3/5, International Renewable Energy Association. (Cited on pages 13 and 132.)

IRENA (2015a). Renewable Energy Policy Brief - Ecuador. Technical Report June, International Renewable Energy Agency. (Cited on page 111.)

IRENA (2015b). Renewable Power Generation Costs in 2014. Technical Report January, International Renewable Energy Agency. (Cited on pages 13, 122, and 137.)

IRENA (2017). Planning for the renewable future Long-term modelling and tools to expand variable renewable power in emerging economies. Technical report, International Renewable Energy Agency. (Cited on pages 18, 134, and 136.)

Isaac, M. and van Vuuren, D. P. (2009). Modeling global residential sector energy demand for heating and air conditioning in the context of climate change. *Energy Policy*, 37(2):507–521. (Cited on page 33.)

Jansen, J., Beurskens, L., and van Tilburg, X. (2006). Application of portfolio analysis to the Dutch generating mix Reference case and two renewables cases : year 2030 - SE and GE scenario. (February):5–67. (Cited on pages 77, 78, 82, and 232.)

Jebaraj, S. and Iniyan, S. (2006). A review of energy models. *Renewable and Sustainable Energy Reviews*, 10(4):281–311. (Cited on pages 48 and 116.)

Jentsch, A., Kreyling, J., and Beierkuhnlein, C. (2007). A new generation of climate-change experiments : events , not trends. *Front Ecol Environ*. (Cited on page 45.)

Jerez, S., Tobin, I., Vautard, R., and Monta, J. P. (2015). The impact of climate change on photovoltaic power generation in Europe. (Cited on page 28.)

Jones, R. N., Chiew, F. H., Boughton, W. C., and Zhang, L. (2006). Estimating the sensitivity of mean annual runoff to climate change using selected hydrological models. *Advances in Water Resources*, 29(10):1419–1429. (Cited on page 93.)

Joode, J. and Boots, M. G. (2005). Concepts of Investment Risks and Strategies in Electricity Generation. Technical Report June, Energy Research Centre - ECN Netherlands. (Cited on page 72.)

Jordan, F. M., Boillat, J.-L., and Schleiss, A. J. (2012). Optimization of the flood protection effect of a hydropower multi-reservoir system. *International Journal of River Basin Management*, 10(1):65–72. (Cited on page 14.)

Kannan, R. and Turton, H. (2011). Documentation on the Development of the Swiss TIMES Electricity Model (STEM-E). Technical Report 11, Paul Scherrer Institut. (Cited on pages 19, 48, 55, and 98.)

Kannan, R. and Turton, H. (2014). Switzerland Energy Transition Scenarios â Development and Application of the Swiss TIMES Energy System Model (STEM). Technical Report 14, Paul Scherrer Institut. (Cited on pages 87, 131, and 279.)

Kanudia, A. and Loulou, R. (1998). Robust responses to climate change via stochastic MARKAL: The case of Québec. *European Journal of Operational Research*, 106(1):15–30. (Cited on page 76.)

Karnauskas, K. B., Lundquist, J. K., and Zhang, L. (2018). Southward shift of the global wind energy resource under high carbon dioxide emissions. *Nature Geoscience*, 11(January):38–44. (Cited on page 27.)

Kaser, G., Grosshauser, M., and Marzeion, B. (2010). Contribution potential of glaciers to water availability in different climate regimes. *Proceedings of the National Academy of Sciences of the United States of America*, 107(47):20223–7. (Cited on page 99.)

Kaser, G., Juen, I., Georges, C., Gómez, J., and Tamayo, W. (2003). The impact of glaciers on the runoff and the reconstruction of mass balance history from hydrological data in the tropical Cordillera Blanca, Perú. *Journal of Hydrology*, 282(1):130–144. (Cited on page 99.)

Kesicki, F. (2012). *Decomposing long-run carbon abatement cost curves - robustness and uncertainty by*. PhD thesis, University College London. (Cited on pages 48 and 72.)

Kesicki, F. and Anandarajah, G. (2011). The role of energy-service demand reduction in global climate change mitigation: Combining energy modelling and decomposition analysis. *Energy Policy*, 39(11):7224–7233. (Cited on page 215.)

Klimenko, V. V., Fedotova, E. V., and Tereshin, A. G. (2018). Vulnerability of the Russian power industry to the climate change. *Energy*, 142:1010–1022. (Cited on page 31.)

Knutti, R. and Sedláček, J. (2012). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, 3(4):369–373. (Cited on pages 39, 40, and 187.)

Köberle, A. C., Gara, R., Cunha, B. S. L., Rochedo, P., Lucena, A. F. P., Szklo, A., and Schae, R. (2018). Are conventional energy megaprojects competitive ? Suboptimal decisions related to cost overruns in Brazil. *Energy Policy*, 122(May 2017):689–700. (Cited on page 4.)

Koomey, J. and Hultman, N. E. (2007). A reactor-level analysis of busbar costs for US nuclear plants, 1970â2005. *Energy Policy*, 35(11):5630–5642. (Cited on page 167.)

Kopytko, N. and Perkins, J. (2011). Climate change, nuclear power, and the adaptationâmitigation dilemma. *Energy Policy*, 39(1):318–333. (Cited on page 30.)

Krey, B. and Zweifel, P. (2008). Efficient Electricity Portfolios for the United States and Switzerland : An Investor View. (Cited on page 80.)

Krey, V. and Riahi, K. (2009). Risk Hedging Strategies under Energy System and Climate Policy Uncertainties. Technical Report August, International Insitute for Applied Systems Analysis. (Cited on pages 80 and 281.)

Krysanova, V., Donnelly, C., Gelfan, A., Gerten, D., Arheimer, B., Hattermann, F., and Kundzewicz, Z. W. (2018). How the performance of hydrological models relates to credibility of projections under climate change. *Hydrological Sciences Journal*, 63(5):696–720. (Cited on pages 70 and 105.)

Krysanova, V., Vetter, T., Eisner, S., Huang, S., Pechlivanidis, I., Strauch, M., Gelfan, A., Kumar, R., Aich, V., Arheimer, B., Chamorro, A., van Griensven, A., Kundu, D., Lobanova, A., VimalMishra, Plotner, S., Reinhardt, J., Seidou, O., Wang, X., Wortmann, M., Zeng, X., and Hattermann, F. (2017). Intercomparison of regional-scale hydrological models and climate change impacts projected for 12 large river basins worldwide â a synthesis. *Environmental Research Letters*. (Cited on page 70.)

Kundzewicz, Mata, Arnel, Döll, Kaba, Jiménez, Miller, Oki, Sen, and Shiklomanov (2007). Freshwater resources and their management. In *Climate Change 2007: Impacts, Adaptation and Vulnerability.*, pages 173–210. (Cited on pages 37, 41, 61, and 189.)

Kundzewicz, Z. W., Krysanova, V., Benestad, R. E., Hov, Ø., Piniewski, M., and Otto, I. M. (2018). Uncertainty in climate change impacts on water resources. *Environmental Science and Policy*, 79(October 2017):1–8. (Cited on pages 38, 66, 70, 71, 72, 187, 251, and 278.)

Kypreos, S. and Lehtila, A. (2014). TIMES-Macro : Decomposition into Hard-Linked LP and NLP Problems. Technical report. (Cited on page 50.)

Labriet, M., Nicolas, C., Tchung-Ming, S., Kanudia, A., and Loulou, R. (2015). Energy Decisions in an Uncertain Climate and Technology Outlook: How Stochastic and Robust Methodologies Can Assist Policy-Makers. In *Informing Energy and Climate Policies Using Energy Systems Models*, pages 69–91. (Cited on pages 75 and 236.)

Latrubesse, E. M., Arima, E. Y., Dunne, T., Park, E., Baker, V. R., D'Horta, F. M., Wight, C., Wittmann, F., Zuanon, J., Baker, P. A., Ribas, C. C., Norgaard, R. B., Filizola, N., Ansar, A., Flyvbjerg, B., and Stevaux, J. C. (2017). Damming the rivers of the Amazon basin. *Nature*, 546(7658):nature22333. (Cited on page 154.)

Lauri, P., Havlík, P., Kindermann, G., Forsell, N., Böttcher, H., and Obersteiner, M. (2014). Woody biomass energy potential in 2050. *Energy Policy*, 66:19–31. (Cited on page 30.)

Lavergne, J.-g. D. D., Vautard, R., Thais, F., Tobin, I., Bre, F., Colette, A., Yiou, P., and Ruti, P. M. (2014). Regional climate model simulations indicate limited climatic impacts by operational and planned European wind farms. pages 1–9. (Cited on page 27.)

Lees, A. C., Peres, C. A., Fearnside, P. M., Schneider, M., and Zuanon, J. A. S. (2016). Hydropower and the future of Amazonian biodiversity. *Biodiversity and Conservation*, 25(3):451–466. (Cited on page 21.)

Lehner, B., Czisch, G., and Vassolo, S. (2005). The impact of global change on the hydropower potential of Europe: A model-based analysis. *Energy Policy*, 33(7):839–855. (Cited on pages 53 and 59.)

Lemos, S. and Botero, S. (2012). Optimización del portafolio de generación hidro-térmico en el mecado eléctrico colombiano. *Dyna*, 175:62–71. (Cited on page 83.)

Li, F. G. N. (2017). Actors behaving badly: Exploring the modelling of non-optimal behaviour in energy transitions. *Energy Strategy Reviews*, 15:57–71. (Cited on pages 63 and 266.)

Li, F. G. N. and Trutnevyte, E. (2017). Investment appraisal of cost-optimal and near-optimal pathways for the UK electricity sector transition to 2050. *Applied Energy*, 189:89–109. (Cited on pages 76 and 80.)

Li, P.-h. and Pye, S. (2018). Assessing the benefits of demand-side flexibility in residential and transport sectors from an integrated energy systems perspective. *Applied Energy*, 228(March):965–979. (Cited on page 212.)

Liang, Y.-C., Chou, C.-C., Yu, J.-Y., and Lo, M.-H. (2016). Mapping the locations of asymmetric and symmetric discharge responses in global rivers to the two types of El Niño. *Environmental Research Letters*, 11(4):044012. (Cited on page 45.)

Lind, A. and Rosenberg, E. (2013). TIMES-Norway Model Documentation. Technical report, Institute for Energy Technology. (Cited on page 98.)

Lind, A., Rosenberg, E., Seljom, P., and Espegren, K. (2013). The Impact of Climate Change on the Renewable Energy Production in Norway. In *2013 International Energy Workshop*. (Cited on pages 56, 60, and 87.)

Linnerud, K., Mideksa, T. K., and Eskeland, G. S. (2011). The Impact of Climate Change on Nuclear Power Supply. *The Energy Journal*, 32(1):149–168. (Cited on page 30.)

Lise, W. and van der Laan, J. (2015). Investment needs for climate change adaptation measures of electricity power plants in the EU. *Energy for Sustainable Development*, 28:10–20. (Cited on page 32.)

Liu, L., Hejazi, M., Li, H., Forman, B., and Zhang, X. (2017). Vulnerability of US thermoelectric power generation to climate change when incorporating state-level environmental regulations. 17109(July):1–5. (Cited on page 24.)

Loaiciga, H. A., Valdes, J. B., Vogel, R., Garvey, J., and Schwarz, H. (1996). Global warming and the hydrologic cycle. *Journal of Hydrology*, 174(1-2):83–127. (Cited on pages 36, 38, and 44.)

Locatelli, G., Mariani, G., Sainati, T., and Greco, M. (2017). Corruption in public projects and megaprojects : There is an elephant in the room ! *International Journal of Project Management*, 35(3):252–268. (Cited on page 85.)

Lopez, V. (2013). The Coca Codo Sinclair hydroelectric project and energy governance in the Ecuadorian Amazon. *Letras Verdes*, pages 1–3. (Cited on page 10.)

Losekann, L., Marrero, G. a., Ramos-Real, F. J., and de Almeida, E. L. F. (2013). Efficient power generating portfolio in Brazil: Conciliating cost, emissions and risk. *Energy Policy*, 62:301–314. (Cited on pages 79, 83, and 265.)

Loulou, R. (2016). Documentation for the TIMES Model PART I. (July):1–151. (Cited on pages 117 and 118.)

Loulou, R. and Kanudia, A. (1999). Minimax regret strategies for greenhouse gas abatement: methodology and application. *Operations Research Letters*, 25(5):219–230. (Cited on page 76.)

Loulou, R. and Labriet, M. (2008). ETSAP-TIAM: The TIMES integrated assessment model Part I: Model structure. *Computational Management Science*, 5(1-2):7–40. (Cited on pages 76, 115, and 280.)

Loulou, R. and Lehtila, A. (2016). Stochastic Programming and Tradeoff Analysis in TIMES. Technical Report May, Energy Technology Systems Analysis Programme. (Cited on page 162.)

Lucena (2010). *Methodological proposal for assessing the vulnerability to climate change in hydropower systems*. PhD thesis, Universidade Federal do Rio de Janeiro. (Cited on pages 4, 17, 47, and 54.)

Lucena, A., Schaeffer, R., Szklo, A., Soria, R., and Chavez, M. (2013). Energy Security in the Amazon. Technical report, UFRJ/COPPE/Energy Planning Program (PPE). (Cited on page 10.)

Lucena, F. P., Hejazi, M., Vasquez-arroyo, E., Turner, S., Daenzer, K., Rochedo, P. R. R., Kober, T., Alexandre, C. K., Cai, Y., Beach, R. H., Gernaat, D., Vuuren, D. P. V., and Zwaan, B. V. D. (2018). Interactions between climate change mitigation and adaptation : The case of hydropower in Brazil. *Energy*, 164. (Cited on pages 55, 60, 75, and 87.)

Lynd, L. R., Liang, X., Biddy, M. J., Allee, A., Cai, H., Foust, T., Himmel, M. E., Laser, M. S., Wang, M., and Wyman, C. E. (2017). Cellulosic ethanol: status and innovation. *Current Opinion in Biotechnology*, 45:202–211. (Cited on page 259.)

Madani, K. and Lund, J. R. (2010). Estimated impacts of climate warming on California's high-elevation hydropower. *Climatic Change*, 102(3):521–538. (Cited on pages 59 and 109.)

MAE (2018). Evaluacion de los impactos del cambio climatico sobre la produccion hidroelectrica en Ecuador. Technical report, Ministerio de Ambiente. (Cited on page 11.)

Magrin, G. O., Marengo, J. A., Boulanger, J.-P., Buckeridge, M. S., Castellanos, E., Poveda, G., Scarano, F. R., Vicuña, S., Alfaro, E., Anthelme, F., Barton, J., Becker, N., Bertrand, A., Confalonieri, U., de Souza, A. P., Demiguel, C., Francou, B., Garreaud, R., Losada, I., McField, M., Nobre, C., Lankao, P. R., Saldiva, P., Samaniego, J. L., Travasso, M., Viglizzo, E., and Villamizar, A. (2014). Central and South America In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report. (Cited on page 64.)

Manne, A. S. (1992). Biomedical and Environmental Assessment Group A linked model for energy-economy analysis. (February). (Cited on page 50.)

Marangoni, G., Tavoni, M., Bosetti, V., Borgonovo, E., Capros, P., Fricko, O., Gernaat, D. E. H. J., Guivarch, C., Havlik, P., Huppmann, D., Johnson, N., and Karkatsoulis, P. (2017). Sensitivity of projected long-term CO 2 emissions across the Shared Socioeconomic Pathways. 7(January):6–8. (Cited on page 75.)

Markoff, M. S. and Cullen, A. C. (2008). Impact of climate change on Pacific Northwest hydropower. *Climatic Change*, 87(3-4):451–469. (Cited on pages 57 and 59.)

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, 7(1):77–91. (Cited on page 77.)

Martínez Ceseña, E., Mutale, J., and Rivas-Dávalos, F. (2013). Real options theory applied to electricity generation projects: A review. *Renewable and Sustainable Energy Reviews*, 19:573–581. (Cited on page 264.)

Martinsen, T. (2011). Introducing technology learning for energy technologies in a national CGE model through soft links to global and national energy models. *Energy Policy*, 39(6):3327–3336. (Cited on page 49.)

Masini, A. and Menichetti, E. (2013). Investment decisions in the renewable energy sector: An analysis of non-financial drivers. *Technological Forecasting and Social Change*, 80(3):510–524. (Cited on page 266.)

Matosovi, M. and Tomši, Ž. (2014). Power generation mix optimization using mean-Lower Partial Moments (LPM) portfolio theory. In *ENERGYCON 2014*, number 1, pages 333–339, Dubrovnik. (Cited on page 83.)

Maurer, E. P. (2007). Uncertainty in hydrologic impacts of climate change in the Sierra Nevada, California, under two emissions scenarios. *Climatic Change*, 82(3-4):309–325. (Cited on page 42.)

Mayer, H. (2007). Calculation and analysis of a hybrid energy input-output table for Germany within the Environmental-Economic Accounting (EEA). *Construction*, (October). (Cited on page 48.)

McCollum, D., Yang, C., Yeh, S., and Ogden, J. (2012). Deep greenhouse gas reduction scenarios for California - Strategic implications from the CA-TIMES energy-economic systems model. *Energy Strategy Reviews*, 1(1):19–32. (Cited on page 116.)

Mcloughlin, E. and Bazilian, M. (2006). Application of Portfolio Analysis to the Irish Electricity Generating Mix in 2020. *Analysis*, (June). (Cited on page 82.)

MCPEC (2016). Politica Industrial del Ecuador. Technical report, Ministerio Coordinador de Produccion, Empleo y Competitividad, Ecuador. (Cited on pages 152 and 157.)

McPhaden, M. J., Zebiak, S. E., and Glantz, M. H. (2006). ENSO as an Integrating Concept in Earth Science. *Science*, 314(5806):1740–1745. (Cited on page 45.)

McPhee, J., Rubio, E., Meza, R., and Ayala, A. (2012). Análisis de Vulnerabilidad del Sector Hidroeléctrico frente a escenarios futuros de cambio climatico en Chile. Technical report, Comision Economica para America Latina y el Caribe Naciones Unidas, Santiago, Chile. (Cited on pages 47, 59, and 71.)

Meehl, G. A., Covey, C., Delworth, T., Latif, M., Mcavaney, B., Mithchell, J. F. B., Stouffer, R. J., and Taylor, K. E. (2007). A New Era in Climate Change Research. *American Meteorological Society*, (September):1383–1394. (Cited on page 39.)

MEER (2013). *Atlas Eólico*, volume 1. (Cited on pages 134, 136, 149, and 151.)

MEER (2014). Atlas Bioenergético de Ecuador. Technical report, Ministerio de Electricidad y Energia Renovable. (Cited on pages 149, 151, and 265.)

MEER (2015). Proyectos de Energia Renovable en el Ecuador. Technical report, Ministerio de Electricidad y Energia Renovable. (Cited on page 104.)

MEER (2017a). Plan Maestro de Electricidad 2016-2025. Technical report, Ministerio de Electricidad y Energia Renovable, Ecuador. (Cited on pages 10, 57, 92, 112, 113, 121, 122, 124, 126, 137, 143, 147, 149, 151, 153, 154, 157, 205, and 283.)

MEER (2017b). Plan Nacional de Eficiencia Energetica. Technical report, Ministerio de Electricidad y Energia Renovable, Ecuador. (Cited on pages 143, 152, 155, and 156.)

Messner, S., Golodnikov, A., and Gritsevskii, A. (1996). A stochastic version of the dynamic linear programming model MESSAGE III. *Energy*, 21(9):775–784. (Cited on pages 80 and 281.)

Messner, S. and Schrattenholzer, L. (2000). MESSAGE-MACRO: Linking an energy supply model with a macroeconomic module and solving it iteratively. *Energy*, 25(3):267–282. (Cited on page 50.)

MICSE (2015). Balance Energetico Nacional 2015 (Base 2014). Technical Report 1, Ministerio Coordinador de Sectores Estrategicos, Quito - Ecuador. (Cited on pages 122 and 147.)

MICSE (2016a). Agenda Nacional de Energia. Technical report, Ministerio Coordinador de Sectores Estrategicos. (Cited on pages 10, 151, and 260.)

MICSE (2016b). Balance Energetico Nacional. Technical report, Ministerio Coordinador de Sectores Estrategicos. (Cited on pages 104 and 111.)

Miller, R. E. and Blair, P. D. (2009). *Input â Output Analysis Foundations and Extensions*. Cambridge University Press, 2nd edition. (Cited on page 48.)

Mills, A. and Wiser, R. (2012). An Evaluation of Solar Valuation Methods Used in Utility Planning and Procurement Processes. Technical Report December, Ernest Orlando Lawrence Berkeley National Laboratory. (Cited on page 134.)

Mirakyan, A. and De Guio, R. (2015). Modelling and uncertainties in integrated energy planning. *Renewable and Sustainable Energy Reviews*, 46:62–69. (Cited on pages 72 and 75.)

Mišic, S. and Radujkovic, M. (2015). Critical drivers of megaprojects success and failure. *Procedia Engineering*, 122(Orsdce):71–80. (Cited on page 13.)

Moss, R., Edmonds, J., Hibbard, K., Manning, M., Rose, S., Van Vuuren, D., Carter, T., Emori, S., Kainuma, M., Kram, T., Meehl, G., Mitchell, J., Nakicenovic, N., Riahi, K., Smith, S., Stouffer, R., Thomson, A., Weyant, J., and Wilbanks, T. (2010). The next generation of scenarios for climate change research and assessment. *Nature*, 463(7282):747–756. (Cited on pages 38 and 251.)

Mouratiadou, I., Biewald, A., Pehl, M., Bonsch, M., Baumstark, L., Klein, D., Popp, A., Luderer, G., and Kriegler, E. (2016). The impact of climate change mitigation on water demand for energy and food: An integrated analysis based on the Shared Socioeconomic Pathways. *Environmental Science & Policy*, 64:48–58. (Cited on page 67.)

MRNNR (2013). *Plan Maestro de Hidrocarburos*. Ecuador. (Cited on pages 148, 149, and 150.)

Mundaca, L., Neij, L., Worrell, E., and McNeil, M. (2010). Evaluating Energy Efficiency Policies with Energy-Economy Models. *Annual Review of Environment and Resources*, 35(1):305–344. (Cited on page 49.)

Muñoz, J. I., Sánchez de la Nieta, A. a., Contreras, J., and Bernal-Agustín, J. L. (2009). Optimal investment portfolio in renewable energy: The Spanish case. *Energy Policy*, 37(12):5273–5284. (Cited on page 78.)

Musgrove, P. (2009). *Wind Power*. Cambridge University Press, Cambridge, UK ; New York, 1 edition edition. (Cited on page 27.)

Nakata, T. (2004). Energy-economic models and the environment. *Progress in Energy and Combustion Science*, 30(4):417–475. (Cited on page 48.)

Nakata, T., Silva, D., and Rodionov, M. (2011). Application of energy system models for designing a low-carbon society. *Progress in Energy and Combustion Science*, 37(4):462–502. (Cited on page 51.)

Nakicenovic, N. and Swart, R. (2000). Summary for Policymakers: Emissions Scenarios. Technical report, Intergovernmental Panel on Climate Change. (Cited on pages 38 and 39.)

Namy, S. (2010). Addressing the Social Impacts of Large Hydropower Dams. *The Journal of International Policy Solutions*, 7:11–17. (Cited on page 21.)

Nearing, G. S., Tian, Y., Gupta, H. V., Clark, M. P., Harrison, K. W., and Weijs, S. V. (2016). A philosophical basis for hydrological uncertainty. *Hydrological Sciences Journal*, 61(9):1666–1678. (Cited on page 66.)

Nemec, J. and Schaake, J. (1982). Sensitivity of water resource systems to climate variation. *Hydrological Sciences Journal*, 27(3):327–343. (Cited on page 37.)

Nerini, F. F., Tomei, J., To, L. S., Bisaga, I., Parikh, P., Black, M., Borrion, A., Spataru, C., Broto, V. C., Anandarajah, G., and Milligan, B. (2018). Mapping synergies and trade-offs between energy and the Sustainable Development Goals. *Nature Energy*, 3(January). (Cited on page 61.)

Nijs, W. and Poncelet, K. (2016). Integrating recurring uncertainties in ETSAP energy system models. Technical Report May, VITO NV. (Cited on pages 79, 80, 83, 162, 175, and 263.)

Noble, I., Huq, S., Anokhin, Y., Carmin, J., Goudou, D., Lansigan, F., Osman-Elasha, B., and Villamizar, A. (2014). Adaptation needs and options. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report. (Cited on page 61.)

NREL (2016). 2016 Annual Technology Baseline. Technical Report PNR-131-2011-014, National Renewable Energy Laboratory, Golden, CO. (Cited on pages 122 and 137.)

OECD/ECLAC/CAF (2015). Latin American Economic Outlook 2016 Outlook 2016. Technical report, Latin American Economic Outlook 2016: Towards a New Partenership with China, Paris. (Cited on page 132.)

Oh, K.-Y., Kim, J.-Y., Lee, J.-K., Ryu, M.-S., and Lee, J.-S. (2012). An assessment of wind energy potential at the demonstration offshore wind farm in Korea. *Energy*, 46(1):555–563. (Cited on page 27.)

OLADE (2017a). *Anuario de 2017 Estadísticas Energéticas*. OLADE, Quito. (Cited on page 132.)

OLADE (2017b). *Manual de Planificación Energética 2017*. Organizacion Latinoamericana de Energia, Ecuador, 2nd edition. (Cited on pages 48 and 49.)

OLADE-BID-AEA (2013). Vulnerabilidad al cambio climático de los sistemas de producción hidroeléctrica en Centroamérica y sus opciones de adaptación. Technical report, OLADE. (Cited on page 52.)

OLADE-IADB (2013). Vulnerabilidad al cambio climatico de los sistemas de produccion hidroelectrica en Centroamerica y sus opciones de adaptacion. Technical Report 0, Latin American Energy Organisation and Inter-American Development Bank. (Cited on page 60.)

OPEC (2017). Annual Statistical Bulletin. Technical report, Organization of the Petroleum Exporting Countries OPEC, Vienna. (Cited on pages 147, 150, 215, and 260.)

Parkinson, S. and Djilali, N. (2015). Robust response to hydro-climatic change in electricity generation planning. *Climatic Change*, pages 1–15. (Cited on pages 5, 33, 42, 54, 57, 60, 159, and 251.)

Pechan, A. and Eisenack, K. (2014). The impact of heat waves on electricity spot markets. *Energy Economics*, 43:63–71. (Cited on page 30.)

Pfenninger, S., Hawkes, A., and Keirstead, J. (2014). Energy systems modeling for twenty-first century energy challenges. *Renewable and Sustainable Energy Reviews*, 33:74–86. (Cited on pages 48 and 116.)

Pfenninger, S. and Staffell, I. (2016). Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. *Energy*, 114:1251–1265. (Cited on page 133.)

Piao, S., Ciais, P., Huang, Y., Shen, Z., Peng, S., Li, J., Zhou, L., Liu, H., Ma, Y., Ding, Y., Friedlingstein, P., Liu, C., Tan, K., Yu, Y., Zhang, T., and Fang, J. (2010). The impacts of climate change on water resources and agriculture in China. *Nature*, 467(7311):43–51. (Cited on page 29.)

Poncelet, K., Delarue, E., Six, D., Duerinck, J., and William, D. (2016). Impact of the level of temporal and operational detail in energy-system planning models. *Applied Energy*, 162:631–643. (Cited on page 136.)

Porter, J., Xie, L., Challinor, A., Cochrane, K., Howden, S., Iqbal, M., Lobell, D., and Travasso, M. (2014). Food Security and Food Production Systems Coordinating. Technical report, IPCC. (Cited on page 29.)

Price, J. and Keppo, I. (2017). Modelling to generate alternatives : A technique to explore uncertainty in energy-environment-economy models. *Applied Energy*, 195:356–369. (Cited on pages 76 and 266.)

Pryor, S. and Barthelmie, R. (2010). Climate change impacts on wind energy: A review. *Renewable and Sustainable Energy Reviews*, 14(1):430–437. (Cited on page 27.)

PSR (2018). PSR. (Cited on page 57.)

Purcell, T. F., Fernandez, N., and Martinez, E. (2017). Rents , knowledge and neo-structuralism : transforming the productive matrix in Ecuador. *Third World Quarterly*, 38(4):914–934. (Cited on page 151.)

Pye, S., Li, F. G. N., Price, J., and Fais, B. (2017). Achieving net-zero emissions through the reframing of UK national targets in the post-Paris Agreement era. *Nature Energy*, 2(3):17–24. (Cited on page 116.)

Pye, S., Sabio, N., and Strachan, N. (2015). An integrated systematic analysis of uncertainties in UK energy transition pathways. *Energy Policy*, 87:673–684. (Cited on pages 5, 168, and 264.)

Rathmann, R., Szklo, A., and Schaeffer, R. (2012). Targets and results of the Brazilian Biodiesel Incentive Program - Has it reached the Promised Land? *Applied Energy*. (Cited on page 48.)

Ray, R., Gallagher, K. P., Lopez, A., and Sanborn, C. (2015). China in Latin America : Lessons for South - South Cooperation and Sustainable Development. Technical Report February, Boston University - Global Economic Governance Initiative. (Cited on page 285.)

Reddy, K. and Clinton, V. (2016). Simulating Stock Prices Using Geometric Brownian Motion : Evidence from Australian Companies Simulating Stock Prices Using Geometric Brownian Motion : Evidence. *Australasian Accounting, Business and Finance Journal*, 10(3):23–47. (Cited on page 169.)

REN21 (2017). Renewables 2017 Global Status Report 2017. Technical report, Renewable Energy Policy Network for the 21st Centrury, Paris. (Cited on page 111.)

Revell, L. (2013). Simulating Brownian motion in R. (Cited on pages 167, 169, 172, and 297.)

Riahi, K., Kriegler, E., Johnson, N., Bertram, C., den Elzen, M., Eom, J., Schaeffer, M., Edmonds, J., Isaac, M., Krey, V., Longden, T., Luderer, G., Méjean, A., McCollum, D. L., Mima, S., Turton, H., van Vuuren, D. P., Wada, K., Bosetti, V., Capros, P., Criqui, P., Hamdi-Cherif, M., Kainuma, M., and Edenhofer, O. (2015). Locked into Copenhagen pledges â Implications of short-term emission targets for the cost and feasibility of long-term climate goals. *Technological Forecasting and Social Change*, 90(Part A):8–23. (Cited on page 122.)

Riahi, K., Vuuren, D. P. V., Kriegler, E., Edmonds, J., Neill, B. C. O., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Crespo, J., Kc, S., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., Ebi, K., Hasegawa, T., Havlik, P., Humpenöder, F., Aleluia, L., Silva, D., Smith, S., Stehfest, E., Bosetti, V., Eom, J., Gernaat, D., Masui, T., Rogelj, J., Stre, J., Drouet, L., Krey, V., Luderer, G., Harmsen, M., Takahashi, K., Baumstark, L., Doelman, J. C., Kainuma, M., Klimont, Z., Marangoni, G., Lotze-campen, H., Obersteiner, M., Tabeau, A., and Tavoni, M. (2017). The Shared

Socioeconomic Pathways and their energy , land use , and greenhouse gas emissions implications : An overview. Technical report. (Cited on pages 138, 139, and 262.)

Rochedo, P. R. R., Soares-Filho, B., Schaeffer, R., Viola, E., Szklo, A., Lucena, A. F. P., Koberle, A., Davis, J. L., Rajão, R., and Rathmann, R. (2018). The threat of political bargaining to climate mitigation in Brazil. *Nature Climate Change*, 8(8):695–698. (Cited on page 259.)

Roques, F., Hiroux, C., and Saguan, M. (2010). Optimal wind power deployment in Europe-A portfolio approach. *Energy Policy*, 38(7):3245–3256. (Cited on page 79.)

Roques, F., Nuttall, W., and Newbery, D. (2006). Using Probabilistic Analysis to Value Power Generation Investments Under Uncertainty. *Cambridge Working Papers in Economics*, (July). (Cited on pages 160, 167, and 168.)

Roques, F. a., Newbery, D. M., and Nuttall, W. J. (2008). Fuel mix diversification incentives in liberalized electricity markets: A Mean-Variance Portfolio theory approach. *Energy Economics*, 30(4):1831–1849. (Cited on pages 78, 79, and 82.)

Ross, S. (2014). *Introduction to Probability Models*. Academic Press. (Cited on page 170.)

Roujol, S. and Joumard, R. (2009). Influence of passenger car auxiliaries on pollutant emission factors within the Artemis model. *Atmospheric Environment*, 43(5):1008–1014. (Cited on page 34.)

Rounsevell, M. D. A. and Metzger, M. J. (2010). Developing qualitative scenario storylines for environmental change assessment. *Wiley Interdisciplinary Reviews: Climate Change*, 1(4):606–619. (Cited on page 73.)

Roy, R., Minville, M., and Demers, C. (2010). Conference on Future Climate and Renewable Energy: Impacts, Risks and Adaptation. In *Conference on Future Climate and Renewable Energy: Impacts, Risks and Adaptation*, number June, Oslo, Norway. Nordic Energy Research NORDEN. (Cited on pages 42, 43, 105, and 252.)

Rübbelke, D. and Vögele, S. (2011). Impacts of climate change on European critical infrastructures: The case of the power sector. *Environmental Science & Policy*, 14(1):53–63. (Cited on page 30.)

Rubinstein, M. (2002). Markowitz's âPortfolio Selectionâ: A Fifty-Year Retrospective. *The Journal of Finance*, 57(3):1041–1045. (Cited on page 78.)

Ruiter, A. (2012). Delta-change approach for CMIP5 GCMs. Technical report, KNMI. (Cited on page 42.)

Samaniego, L., Kumar, R., Breuer, L., Chamorro, A., Flörke, M., Pechlivanidis, I. G., Schäfer, D., Shah, H., Vetter, T., Wortmann, M., and Zeng, X. (2016). Propagation of forcing and model uncertainties on to hydrological drought characteristics in a multi-model century-long experiment in large river basins. *Climatic Change*. (Cited on page 185.)

Sathaye, J., Dale, L., Larsen, P., Fitts, G., Franco, G., and Spiegel, L. (2012). Estimating risk to California energy infrastructure from projected climate change. Technical report, Lawrence Berkeley National Laboratory. (Cited on pages 30, 32, and 207.)

Sathaye, J. a., Dale, L. L., Larsen, P. H., Fitts, G. a., Koy, K., Lewis, S. M., and Lucena, A. F. P. D. (2011). Estimating Risk To California Energy Infrastructure From Projected Climate Change. Technical report, Lawrence Berkeley National Laboratory. (Cited on page 33.)

Schaeffer, R., Szklo, A., De Lucena, A., Soria, R., and Chavez-Rodriguez, M. (2013). The Vulnerable Amazon: The Impact of Climate Change on the Untapped Potential of Hydropower Systems. *IEEE Power and Energy Magazine*, 11(3):22–31. (Cited on pages 3, 8, and 154.)

Schaeffer, R., Szklo, A. S., and Lucena, A. (2009). Climate Change and Energy Security in Brazil. In *World Bank Energy Week*, Rio de Janeiro - Brasil. (Cited on pages 24 and 31.)

Schaeffer, R., Szklo, A. S., Pereira de Lucena, A. F., Moreira Cesar Borba, B. S., Pupo Nogueira, L. P., Fleming, F. P., Troccoli, A., Harrison, M., and Boulahya, M. S. (2012). Energy sector vulnerability to climate change: A review. *Energy*, 38(1):1–12. (Cited on pages 26, 29, 62, and 208.)

Seljom, P., Rosenberg, E., Fidje, A., Erik, J., Meir, M., Rekstad, J., and Jarlset, T. (2011). Modelling the effects of climate change on the energy system â A case study of Norway. *Energy Policy*, 39(11):7310–7321. (Cited on pages 47, 54, 55, 56, 59, 72, 87, 109, and 134.)

Seljom, P. and Tomasgard, A. (2015). Short-term uncertainty in long-term energy system models â A case study of wind power in Denmark. *Energy Economics*, 49:157–167. (Cited on pages 5, 75, 264, and 279.)

Seljom, P. and Tomasgard, A. (2017). The impact of policy actions and future energy prices on the cost-optimal development of the energy system in Norway and Sweden. *Energy Policy*, 106:85–102. (Cited on pages 131 and 266.)

SENAGUA (2009). Delimitación y codificación de unidades geográficas del Ecuador. Technical report, Secretaría Nacional del Agua de Ecuador. (Cited on page 99.)

Sengupta, C. (2004). *Financial modeling using excel and VBA*, volume 152. John Wiley & Sons. (Cited on pages 167 and 170.)

SENPLADES (2009). Plan Nacional para el Buen Vivir 2009 - 2013. Technical report, Secretaria Nacional de Planificacion y Desarrollo, Quito - Ecuador. (Cited on page 151.)

SENPLADES (2012). Transformacion de la Matriz Productiva - Folleto Informativo. Technical report, Secretaria Nacional de Planificacion y Desarrollo. (Cited on page 151.)

SENPLADES (2017). Plan Nacional de Desarrollo 2017-2021. Technical report, Secretaria Nacional de Planificacion y Desarrollo. (Cited on page 151.)

Serrat-Capdevila, A., Valdes, J. B., Perez, J. G., Baird, K., Mata, L. J., and Maddock III, T. (2007). Modeling climate change impacts â and uncertainty â on the hydrology of a riparian system : The San Pedro Basin (Arizona / Sonora). pages 48–66. (Cited on page 43.)

Shadman, F., Sadeghipour, S., Moghavvemi, M., and Saidur, R. (2016). Drought and energy security in key ASEAN countries. *Renewable and Sustainable Energy Reviews*, 53:50–58. (Cited on page 30.)

Shamir, E., Megdal, S. B., Carrillo, C., Castro, C. L., Chang, H.-i., Chief, K., Corkhill, F. E., Eden, S., Georgakakos, K. P., Nelson, K. M., and Prietto, J. (2015). Climate change and water resources management in the Upper Santa Cruz River , Arizona. *JOURNAL OF HYDROLOGY*, 521:18–33. (Cited on page 43.)

Shrestha, S., Bajracharya, A. R., and Babel, M. S. (2016). Assessment of risks due to climate change for the Upper Tamakoshi Hydropower Project in Nepal. *Climate Risk Management*, 14:27–41. (Cited on pages 60 and 72.)

Simpson, A. (2013). Challenging hydropower development in Myanmar (Burma): cross-border activism under a regime in transition. *The Pacific Review*, 26(2):129–152. (Cited on page 21.)

SINEA (2015). Declaración de Santiago para la Interconexion e Integracion Electrica Andina. (Cited on page 144.)

Smith, L. A. and Petersen, A. C. (2014). Variations on reliability: connecting climate predictions to climate policy. *Error and uncertainty in scientific practice*, (1972):137–156. (Cited on pages 188 and 250.)

Solano, B. and Pye, S. (2015). OVERVIEW OF THE EUROPEAN TIMES MODEL AT UNIVERSITY COLLEGE LONDON (ETM-UCL). Technical Report May. (Cited on page 140.)

Solaymani, S. and Kari, F. (2014). Impacts of energy subsidy reform on the Malaysian economy and transportation sector. *Energy Policy*, 70:115–125. (Cited on page 49.)

Soria, R., Lucena, F. P., Tomaschek, J., Fichter, T., Haasz, T., Szklo, A., Schaeffer, R., Rochedo, P., Fahl, U., and Kern, J. (2016). Modelling concentrated solar power (CSP) in the Brazilian energy system : A soft-linked model coupling approach. *Energy*, 116. (Cited on pages 50, 134, and 256.)

Sovacool, B. K., Gilbert, A., and Nugent, D. (2014a). An International Comparative Assessment of Construction Cost Overruns for Electricity Infrastructure. *Energy Research & Social Science*, 3:152–160. (Cited on pages 14, 15, 84, 85, 173, 174, and 224.)

Sovacool, B. K., Gilbert, A., and Nugent, D. (2014b). Risk, Innovation, Electricity Infrastructure and Construction Cost Overruns: Testing Six Hypotheses. *Energy*, 74:906–917. (Cited on pages 4 and 14.)

Sovacool, B. K., Nugent, D., and Gilbert, A. (2014c). Construction Cost Overruns and Electricity Infrastructure: An Unavoidable Risk? *The Electricity Journal*, 27(4):112–120. (Cited on page 154.)

Spalding-Fecher, R., Joyce, B., and Winkler, H. (2017). Climate change and hydropower in the Southern African Power Pool and Zambezi River Basin : System-wide impacts and policy implications. *Energy Policy*, 103(June 2016):84–97. (Cited on pages 57, 60, 72, and 253.)

Spinney, P. J. and Watkins, G. C. (1996). Monte Carlo simulation techniques and electric utility resource decisions. *Energy Policy*, 24(2):155–163. (Cited on page 168.)

Sridharan, V., Broad, O., Shivakumar, A., Howells, M., Boehlert, B., Groves, D. G., Rogner, H.-h., Taliotis, C., Neumann, J. E., Strzepek, K. M., Lempert, R., Joyce, B., Huber-lee, A., and Cervigni, R. (2019). Resilience of the Eastern African electricity sector to climate driven changes in hydropower generation. *Nature Communications*, pages 1–9. (Cited on pages 55 and 60.)

Srinivasan, R., Zhang, X., and Arnold, J. (2010). SWAT Ungauged: Hydrological Budget and Crop Yield Predictions in the Upper Mississippi River Basin. *Transactions of the ASABE*, 53(5):1533. (Cited on page 96.)

Srivastava, A. K., Mboh, C. M., Zhao, G., Gaiser, T., and Ewert, F. (2018). Climate change impact under alternate realizations of climate scenarios on maize yield and biomass in Ghana. *Agricultural Systems*, 159:157–174. (Cited on page 29.)

Staffell, I. and Pfenninger, S. (2016). Using bias-corrected reanalysis to simulate current and future wind power output. *Energy*, 114:1224–1239. (Cited on page 133.)

Stirling, A. (2010). Multicriteria diversity analysis. *Energy Policy*, 38(4):1622–1634. (Cited on page 80.)

Systematic-investor (2012). Simulating Multiple Asset Paths in R. (Cited on pages 172 and 297.)

Tattini, J. (2015). *Modeling of the Norwegian power system and analysis of the power trade in the Nordic countries*. PhD thesis, Danish Technical University. (Cited on pages 117 and 129.)

Taylor, K. E., Stouffer, R. J., and Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, 93(4):485–498. (Cited on pages 37, 38, 42, 251, and 252.)

Tegegne, G., Park, D. K., and Kim, Y.-o. (2017). Comparison of hydrological models for the assessment of water resources in a data-scarce region , the Upper Blue Nile River Basin. *Journal of Hydrology: Regional Studies*, 14(November):49–66. (Cited on page 43.)

Tekiner, H., Coit, D. W., and Felder, F. A. (2010). Multi-period multi-objective electricity generation expansion planning problem with Monte-Carlo simulation. *Electric Power Systems Research*, 80(12):1394–1405. (Cited on page 168.)

Teotonio, C., Fortes, P., Roebeling, P., Rodriguez, M., and Robaina-alves, M. (2017). Assessing the impacts of climate change on hydropower generation and the power sector in Portugal : A partial equilibrium approach. *Renewable and Sustainable Energy Reviews*, 74(February):788–799. (Cited on pages 5, 17, 42, 54, 55, 56, 60, 87, 109, 116, 137, and 279.)

Teutschbein, C. and Seibert, J. (2012). Bias correction of regional climate model simulations for hydrological climate-change impact studies : Review and evaluation of different methods. *Journal of Hydrology*, 456-457:12–29. (Cited on page 41.)

The InterAmerican Dialogue (2016). China Latina America Financing Database. Technical report. (Cited on pages 10 and 283.)

Thompson, J., Laizé, C., a.J. Green, Acreman, M., and Kingston, D. (2014). Climate change uncertainty in environmental flows for the Mekong River. *Hydrological Sciences Journal*, 59(3-4):935–954. (Cited on page 42.)

Thompson, J. R., Crawley, A., and Kingston, D. G. (2015). GCM-related uncertainty for river flows and inundation under climate change: the Inner Niger Delta. *Hydrological Sciences Journal*, 6667(July):02626667.2015.1117173. (Cited on pages 184 and 185.)

Thompson, J. R., Green, A. J., Kingston, D. G., and Gosling, S. N. (2013). Assessment of uncertainty in river flow projections for the Mekong River using multiple GCMs and hydrological models. *Journal of Hydrology*, 486(1-30). (Cited on page 71.)

Thomson, A. M., Calvin, K. V., Smith, S. J., Kyle, G. P., Volke, A., Patel, P., Delgado-Arias, S., Bond-Lamberty, B., Wise, M. A., Clarke, L. E., and Edmonds, J. A. (2011). RCP4.5: A pathway for stabilization of radiative forcing by 2100. *Climatic Change*, 109(1):77–94. (Cited on pages 109 and 185.)

Thorsteinsson, T. and Björnsson, H. (2011). Climate change and energy systems: Impacts, Risks and Adaptation in the Nordic and Baltic countries. Technical report, Nordic Council of Ministers, Copenhagen. (Cited on page 59.)

Tilmant, A., Goor, Q., and Pinte, D. (2009). Agricultural-to-hydropower water transfers : sharing water and benefits in hydropower-irrigation systems. *Hydrology and Earth System Sciences*, 13:1091–1101. (Cited on page 14.)

Tol, R. S. J., Fankhauser, S., and Smith, J. B. (1998). The scope for adaptation to climate change: what can we learn from the impact literature? *Global Environmental Change*, 8(2):109–123. (Cited on pages 62 and 63.)

Trouet, V. and Van Oldenborgh, G. J. (2013). KNMI Climate Explorer: A Web-Based Research Tool for High-Resolution Paleoclimatology. *Tree-Ring Research*, 69(1):3–13. (Cited on pages 105 and 184.)

Trutnevyte, E. (2016). Does cost optimization approximate the real-world energy transition? *Energy*, 106:182–193. (Cited on page 76.)

Trutnevyte, E., Mcdowall, W., Tomei, J., and Keppo, I. (2016). Energy scenario choices : Insights from a retrospective review of UK energy futures. *Renewable and Sustainable Energy Reviews*, 55:326–337. (Cited on page 74.)

Tundisi, J. G., Goldemberg, J., Matsumura-Tundisi, T., and Saraiva, A. C. F. (2014). How many more dams in the Amazon? *Energy Policy*, 74(Supplement C):703–708. (Cited on page 154.)

Turner, S. W. D. and Galelli, S. (2016). Water supply sensitivity to climate change: An R package for implementing reservoir storage analysis in global and regional impact studies. *Environmental Modelling and Software*, 76:13–19. (Cited on page 19.)

Ty, P. H., Van Westen, A. C. M., and Zoomers, A. (2013). Compensation and Resettlement Policies after Compulsory Land Acquisition for Hydropower Development in Vietnam: Policy and Practice. *Land*, 2(4):678–704. (Cited on page 21.)

UN (2015). Transforming our world: the 2030 Agenda for Sustainable Development. Technical Report October, United Nations General Assembly. (Cited on page 3.)

UNFCCC (2015a). Adoption of the Paris Agreement Proposal by the President. Technical Report November, United Nations Framework Convention on Climate Change, Paris. (Cited on pages 3, 109, and 185.)

UNFCCC (2015b). Ecuador's Intended Nationally Determined Contribution (INDC). Technical report, United Nations Framework Convention for Climate Change. (Cited on pages 10, 152, 153, 155, 259, and 265.)

US NSA (1977). *Climate, Climatic Change, and Water Supply*. The National Academies Press, Washington, DC. (Cited on page 37.)

Usher, W. and Strachan, N. (2012). Critical mid-term uncertainties in long-term decarbonisation pathways. *Energy Policy*, 41:433–444. (Cited on pages 74, 76, 172, 222, and 265.)

Usher, W. and Strachan, N. (2013). An expert elicitation of climate, energy and economic uncertainties. *Energy Policy*, 61:811–821. (Cited on page 167.)

van Beeck, N. (2003). *A New Decision Support Method for Local Energy Planning in Developing Countries*. PhD thesis, Tilburg University. (Cited on page 49.)

van der Zwaan, B., Boccalon, A., and Dalla, F. (2018). Prospects for hydropower in Ethiopia : An energy-water nexus analysis. *Energy Strategy Reviews*, 19:19–30. (Cited on pages 17, 55, 56, 60, 87, and 253.)

van Notten, P. W., Rotmans, J., van Asselt, M. B., and Rothman, D. S. (2003). An updated scenario typology. *Futures*, 35(5):423–443. (Cited on page 73.)

van Oldenborgh, G., Collins, M., Arblaster, J., Christensen, J., Marotzke, J., Power, S., Rummukainen, M., and Zhou, T. (2013). Annex I: Atlas of Global and Regional Climate Projections. Technical report, IPCC. (Cited on pages 109 and 185.)

van Vliet, M. T. H., Wiberg, D., Leduc, S., and Riahi, K. (2016a). Power-generation system vulnerability and adaptation to changes in climate and water resources - Supplementary Information. *Nature Climate Change*, Supplement(January). (Cited on pages 5, 52, 57, 60, 62, 67, 68, and 69.)

van Vliet, M. T. H., Wiberg, D., Leduc, S., and Riahi, K. (2016b). Power-generation system vulnerability and adaptation to changes in climate and waterÂ resources. *Nature Climate Change*, (January). (Cited on pages 4 and 185.)

van Vuuren, D. P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G. C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S. J., and Rose, S. K. (2011). The representative concentration pathways: an overview. *Climatic Change*, 109(1-2):5–31. (Cited on pages 39, 40, 41, 91, and 105.)

van Vuuren, D. P., Stehfest, E., Gernaat, D. E. H. J., van den Berg, M., Bijl, D. L., de Boer, H. S., Daioglou, V., Doelman, J. C., Edelenbosch, O. Y., Harmsen, M., Hof, A. F., and van Sluisveld, M. A. E. (2018). Alternative pathways to the 1.5âÂ°C target reduce the need for negative emission technologies. *Nature Climate Change*, 8(5):391–397. (Cited on page 261.)

Vergara, W., Deeb, A. M., Valencia, A. M., Bradley, R. S., Francou, B., Zarzar, A., Grünwaldt, A., and Haeussling, S. M. (2007). Economic Impacts of Rapid Glacier Retreat in the Andes. *Eos, Transactions American Geophysical Union*, 88(25):261. (Cited on page 99.)

Vetter, T., Huang, S., Aich, V., Yang, T., Wang, X., Krysanova, V., and Hattermann, F. (2015). Multi-model climate impact assessment and intercomparison for three large-scale river basins on three continents. *Earth System Dynamics*, 6(1):17–43. (Cited on page 75.)

Vetter, T., Reinhardt, J., Flörke, M., van Griensven, A., Hattermann, F., Huang, S., Koch, H., Pechlivanidis, I. G., Plötner, S., Seidou, O., Su, B., Vervoort, R. W., and Krysanova, V. (2017). Evaluation of sources of uncertainty in projected hydrological changes under climate change in 12 large-scale river basins. *Climatic Change*, 141(3):419–433. (Cited on pages 67 and 70.)

Vicuña, S., Dracup, J. a., and Dale, L. (2011). Climate change impacts on two high-elevation hydropower systems in California. *Climatic Change*, 109(S1):151–169. (Cited on page 59.)

Vicuna, S., Leonardson, R., Hanemann, M. W., Dale, L. L., and Dracup, J. a. (2008). Climate change impacts on high elevation hydropower generation in California's Sierra Nevada: A case study in the Upper American River. *Climatic Change*, 87(1 SUPPL):123–137. (Cited on pages 54 and 59.)

Villavicencio, A. (2015). Un cambio de matriz energética bajo toda sospecha. (Cited on page 11.)

Vithayasrichareon, P. (2012). *Portfolio-Based Decision-Support Tool for Generation Investment and Planning in Uncertain and Low-Carbon Future Electricity Industries*. PhD thesis, University of New South Wales. (Cited on pages 72, 79, and 160.)

Vithayasrichareon, P. and MacGill, I. F. (2012). Portfolio assessments for future generation investment in newly industrializing countries â A case study of Thailand. *Energy*, 44(1):1044–1058. (Cited on page 82.)

Vithayasrichareon, P., Riesz, J., and MacGill, I. (2014). Assessing Long-term Security of Electricity Supply and the Role of Renewable Energy: A Probabilistic Generation Portfolio Analysis Approach. In *Paper submission for the 4th IAEE Asian Conference, Beijing, China Assessing*, pages 1–10, Beijing - China. (Cited on page 159.)

Vithayasrichareon, P., Riesz, J., and MacGill, I. F. (2015). Using renewables to hedge against future electricity industry uncertaintiesâAn Australian case study. *Energy Policy*, 76:43–56. (Cited on pages 5, 79, 80, 83, 168, and 232.)

Vizhñay, P. (2013). La Matriz Energética Ecuatoriana. In *PRIMER CONGRESO INTERNACIONAL EXPO CIENTIFICA - INVESTIGACION SOSTENIBLE, ENERGIAS RENOVABLES Y EFICIENCIA ENERGETICA*, pages 1–10, Quito - Ecuador. INER. (Cited on page 113.)

Vogt-Schilb, A. and Hallegatte, S. (2011). When Starting with the Most Expensive Option Makes Sense Use and Misuse of Marginal Abatement Cost Curves. (Cited on page 61.)

Vogt-Schilb, A., Hallegatte, S., and De Gouvello, C. (2014). Long-term mitigation strategies and marginal abatement cost curves: a case study on Brazil. (Cited on page 122.)

Vuille, M. (2013). Climate Change and Water Resources in the Tropical Andes. Technical Report March, Inter-American Development Bank. (Cited on page 65.)

Wagner, H.-J. and Mathur, J. (2011). *Introduction to Hydro Energy Systems: Basics, Technology and Operation*. Green Energy and Technology. Springer-Verlag, Berlin Heidelberg. (Cited on page 53.)

Ward, P. J., Jongman, B., Kummu, M., Dettinger, M. D., Weiland, F. C. S., and Winsemius, H. C. (2014). Strong influence of El Niño Southern Oscillation on flood risk around the world. *Proceedings of the National Academy of Sciences*, 111(44):15659–15664. (Cited on pages 45 and 254.)

Ward, P. R. B., Timo, A., Meynell, P. J., and Ketelsen, T. (2013). Flood control challenges for large hydro-electric reservoirs. Technical report, CPWF Mekong. (Cited on page 14.)

WEC (2004). Comparison of energy systems using life cycle assessment. Technical Report July, World Energy Council. (Cited on page 18.)

WEC (2015a). Charting the Upsurge in Hydropower Development. Technical report, World Energy Council. (Cited on pages 20 and 271.)

WEC (2015b). Charting the Upsurge in Hydropower Development - Key Messages. Technical report, World Energy Council. (Cited on page 7.)

WEC (2016). World Energy Resources Hydropower | 2016. Technical report, World Energy Council. (Cited on page 12.)

Welsch, M., Deane, P., Howells, M., Gallachóir, B. Ó., Rogan, F., Bazilian, M., and Rogner, H.-h. (2014). Incorporating flexibility requirements into long-term energy system models â A case study on high levels of renewable electricity penetration in Ireland q. *Applied Energy*, 135:600–615. (Cited on page 136.)

Westner, G. and Madlener, R. (2011). Development of cogeneration in Germany: A mean-variance portfolio analysis of individual technology's prospects in view of the new regulatory framework. *Energy*, 36(8):5301–5313. (Cited on page 78.)

Wilbanks, T., Bhatt, V., and Bilello, D. (2008). Effects of climate change on energy production and use in the United States. Technical Report February. (Cited on pages 24, 31, 32, and 34.)

Wilkinson, A. and Eidinow, E. (2008). Evolving practices in environmental scenarios: a new scenario typology. *Environmental Research Letters*, 3(4):045017. (Cited on page 73.)

Wilson, I. (2000). From Scenario Thinking to Strategic Action. *Technological Forecasting and Social Change*, 65(1):23–29. (Cited on page 73.)

Winemiller, K. O., McIntyre, P. B., Castello, L., Fluet-Chouinard, E., Giarrizzo, T., Nam, S., Baird, I. G., Darwall, W., Lujan, N. K., Harrison, I., Stiassny, M. L. J., Silvano, R. A. M., Fitzgerald, D. B., Pelicice, F. M., Agostinho, A. A., Gomes, L. C., Albert, J. S., Baran, E., Petrere, M., Zarfl, C., Mulligan, M., Sullivan, J. P., Arantes, C. C., Sousa, L. M., Koning, A. A., Hoeinghaus, D. J., Sabaj, M., Lundberg, J. G., Armbruster, J., Thieme, M. L., Petry, P., Zuanon, J., Vilara, G. T., Snoeks, J., Ou, C., Rainboth, W., Pavanelli, C. S., Akama, A., Soesbergen, A. v., and Saenz, L. (2016). Balancing hydropower and biodiversity in the Amazon, Congo, and Mekong. *Science*, 351(6269):128–129. (Cited on pages 8, 21, and 154.)

Wiser, R., Yang, Z., Hand, Hohmeyer, Infield, Jensen, Nikolaev, O'Malley, Sinden, and Zervos (2011). Wind Energy. In IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation [O. Edenhofer, R. Pichs-Madruga, Y. Sokona, K. Seyboth, P. Matschoss, S. Kadner, T. Zwickel, P. Eickemeier, G. Hansen, S. Schlömer, C. von Stechow (eds)]. Technical report. (Cited on page 27.)

Wisser, D., Frolking, S., Hagen, S., and Bierkens, M. F. P. (2013). Beyond peak reservoir storage ? A global estimate of declining water storage capacity in large reservoirs. *Water Resources Research*, 49(July):5732–5739. (Cited on pages 19 and 253.)

Wood, A. W., Leung, L. R., Sridhar, V., and Lettenmaier, D. P. (2004). Hydrologic Implications of Dynamical and Statistical Approaches to Downscaling Climate Model Outputs. *Climatic Change*, 62(1-3):189–216. (Cited on page 42.)

World Bank Group (2013). Interim Technical Note: Greenhouse Gases from Reservoirs Caused by Biochemical Processes. Technical report, The World Bank Group. (Cited on page 18.)

World Commission on Dams (2000). *Dams and Development: A New Framework for Decision-making: the Report of the World Commission on Dams*. Earthscan. (Cited on page 84.)

Xu, C.-y. (1999). Climate Change and Hydrologic Models: A Review of Existing Gaps and Recent Research Developments. *Water Resources Management*, 13(5):369–382. (Cited on pages 38 and 44.)

Yan, D., Werners, S. E., and Ludwig, F. (2015). Hydrological response to climate change : The Pearl River , China under different RCP scenarios. *Journal of Hydrology : Regional Studies*, 4:228–245. (Cited on page 43.)

Yates, D. and Strzepek, K. (1994). Potential Evapotranspiration Methods and their Impact on the Assessment of River Basin Runoff Under Climate Change. (Cited on pages 94 and 95.)

Yi Ng, J., Turner, S., and Galelli, S. (2017). Influence of El Nino Southern Oscillation on global hydropower production. *Environmental Research LettersEnvironmental Research Letters*. (Cited on pages 98, 190, and 254.)

Yu, J.-Y. and Zou, Y. (2013). The enhanced drying effect of Central-Pacific El Niño on US winter. *Environmental Research Letters*, 8(1):014019. (Cited on page 45.)

Zambrano-Barragen, P. (2012). *The Role of the State in Large-Scale Hydropower Development. Perspectives from Chile, Ecuador, and Peru*. PhD thesis, MASSACHUSETTS INSTITUTE OF TECHNOLOGY. (Cited on page 151.)

Zeng, R., Cai, X., RIngler, C., and Zhu, T. (2017). Hydropower versus irrigation â an analysis of global patterns. *Environmental Research Letters*. (Cited on page 14.)

Zeng, Y., Cai, Y., Huang, G., and Dai, J. (2011). A Review on Optimization Modeling of Energy Systems Planning and GHG Emission Mitigation under Uncertainty. *Energies*, 4(12):1624–1656. (Cited on page 51.)

Zeyringer, M., Price, J., Fais, B., Li, P.-h., and Sharp, E. (2018). Designing low-carbon power systems for Great Britain in 2050 that are robust to the spatiotemporal and inter-annual variability of weather. *Nature Energy*, 3(May). (Cited on page 27.)

Zhu, L. and Fan, Y. (2010). Optimization of China's generating portfolio and policy implications based on portfolio theory. *Energy*, 35(3):1391–1402. (Cited on pages 79 and 82.)

COLOPHON

This document was typeset using the typographical look-and-feel classicthesis developed by André Miede. The style was inspired by Robert Bringhurst's seminal book on typography *"The Elements of Typographic Style"*.